Effectively Implementing an Online Homework and Testing Management System to Increase Student Achievement - A Student Tailored Pedagogical Approach

By

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ABSTRACT

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Turning to online educational technology is a growing trend in our society. In particular, many community college Mathematics Departments have adopted online preparation and rigorous enhancement platform (OPREP) such as WebAssign. Nationally educators are attempting to address the low passing rates in developmental mathematics. Developmental mathematics courses are the gatekeepers to higher education. Slow progression through these courses can adversely affect a student's ability to persist to graduation, which in turn impacts an individual's employment opportunities and quality of life. The literature shows that OPREPs are typically employed to replace the tedious and time-consuming task of grading paper-based homework. Ignoring the testing management features of an OPREP and limiting it to a web-based homework tool is a reflection on implementation strategy. The purpose of this research is to develop a grounded theory about effectively implementing OPREP, which is informed by the perspectives and beliefs of the developmental mathematics students who use them. This mixed method study critically analyzed the student comment sheets, student evaluations, and the responses from 129 Elementary Algebra students who completed a questionnaire about their experiences using WebAssign. Analysis through an adult learning theory lens revealed the central phenomenon of the students' needs for immediate feedback and the role that feedback plays in facilitating self-regulated learning.

The findings reveal that the nature of the feedback extended beyond correctness. Students preferred to use interactive step-by-step tutorials, practicing different versions of the problem and watching lectures more than any other learning tool.

The instructor's implementation was a point of emphasis for key students. Multiple repeaters of elementary algebra stressed the importance of the OPREP implementation strategy on their achievement. Comments range from differences in the availability and strategic deployment of the learning tools to proper instruction on how a student should use the OPREP. Although this study confirms a significant and relative large correlation between homework and an exit examination, it also shows that OPREP assessments such as quizzes and practice examinations have stronger positive correlations. Results showed that OPREP quiz average was the best sole predictor of student achievement. OPREP quiz average was also the only OPREP assignment category included as a predictor of student achievement in the best multiple linear regression model.

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CHAPTER I
INTRODUCTION

Societal Issue: Developmental Mathematics Passing Rates

Low passing rates in developmental mathematics have plagued educational institutions (especially community colleges) in the United States for years and the need for pedagogical change is evident. As of the fall 2000 semester 12% of the mathematics classes at four-year colleges and 57% at two-year colleges were remedial courses (McGowen, 2006). In the United States, the DWF (a grade of “D”, “W” or “F”) rate of students taking algebra is between 40-50% and in some populations has been reported as high as 90% (Benford & Gess-Newsome, 2006; Herriott, 2006). These remedial courses are the gatekeepers to higher education, and repeated failure of these courses can often result in stagnant students who give up on their education or burn through their financial aid in vain. The call for innovation when revamping existing curricula has increased due to President Obama’s plan to invest approximately $12 billion in community colleges through the American Graduation Initiative (Brandon, 2009). Nationally, many educators have turned to online preparation and rigorous enhancement platform (OPREP) as part of the strategy of addressing this crisis. These include institution-developed software (e.g., Virginia Tech’s Mathematics Emporium), freely available systems (e.g., WeBWorK, DRILL), commercial products (e.g., WebAssign, MapleTA, MyMathLab) and adaptive learning systems (e.g., ALEKS, HAWKES).

Though many institutions are incorporating OPREP, the American Mathematical Society’s (AMS) report on their 2009 Homework Software Survey shows the lack of consensus about the extent and nature of technology’s role in the curriculum. In the last decade, several scholars have compared “web-based versus paper-based homework” with inconsistent results

(Clarke, 2011, p. 85). These quantitative comparative studies used a traditional classroom control group versus a treatment group using an OPREP. Their results were inconsistent and sometimes contradictory, ranging from no statistically significant results to a possibly positive effect or negative impact on student achievement. Two apparent gaps in the research arise from the failure to examine the students' experiences using OPREP (in terms of their preferred OPREP functionality), and the lack of information about effective detailed and institution specific implementation strategies.

All OPREP mentioned above have the following characteristics or functionality. An OPREP requires students to log in to a website to access their assignments and enter their answers. The systems typically have different question types (e.g., numerical, multiple choice, fill in the blank, multiple select) and accept numerical answers as well as algebraic expressions. Instructors can typically choose questions (or pools of questions) from question banks, which may be associated with textbooks. Algorithmically generated questions can individualize assignments by providing similar questions with that same level of difficulty but different numbers. Some OPREPs allow instructors to control the number of submissions permitted per question as well as the students' access to feedback (i.e., answer key, solution key) and learning tools (e.g., electronic textbook, video lectures, step by step tutorials).

The AMS' report on their 2009 Homework Software Survey assesses the experiences of departments using homework software, and explains the concerns of departments that were considering such software. Of the 467 responding departments (out of 1230 surveyed), 260 departments had used such software and 98 departments identified themselves as 'disinterested'. Current users were more positive about the benefits of homework software than prospective users and much less concerned about drawbacks than prospective users. The primary benefit of using the systems was better student learning, the primary drawback being students not showing their work. Initial faculty resistance to using homework software occurred in most departments. Students and non-tenure-track faculty were more receptive to the software than tenured/tenure-track faculty. Shelton (2013) wrote, “Longstanding skepticism of technology in education, combined with inadequate training and support, has also thwarted the widespread adoption and use of education technology” (p. 9).

Conceptual and Methodological Frameworks

One promising avenue to understanding the student experiences is a qualitative method called grounded theory, where the central phenomena of the student experience are grounded in the data and revealed through triangulation of several data sources. Grounded theory uses the viewpoints of the participants (in this case, anonymous students) to develop theory about a process or action. In 1967, systematic grounded theory was introduced by Glaser and Strauss. They introduced the method as a contrast to a priori theoretical orientations in sociology; Glaser and Strauss “held that theories should be ‘grounded’ in data from the field, especially in the actions, interactions, and social processes of people” (Miller & Salkind, 2002, p. 152). Strauss’ systematic approach to grounded theory is stringent because it consists of prescribed categories when coding data. This study used Charmaz’s (2005) constructivist approach to grounded theory because it affords more flexibility during open coding, axial coding and selective coding phases of analysis. Grounded theory is both a qualitative approach and a method of data analysis so the implications are grounded in the students’ experiences. It is applicable to both qualitative and quantitative research studies.

The poor passing rates in developmental mathematics cannot be ignored and critically analyzing the commonalities in the student experiences as well as student performances may hold the keys to change. States across the nation have begun to hold higher learning institutions accountable for their ability to graduate students. Institutions have turned their focus on searching for effective ways to increase student persistence toward graduation. Improving support services, developing learning communities, implementing early intervention processes, revamping the curriculum and using innovations in pedagogy are among some of the emerging trends. Specifically, developmental courses (e.g., Elementary Algebra) are the gatekeepers to higher education and slow progression through these courses can adversely affect graduation rates. Earning a college degree has immense implications for an individual's employment opportunities and quality of life.

The researcher is using a social constructivism framework with a philosophical/ theoretical lens of adult learning theory. Adult learners participate in many types of formal and informal education activities that they hope will help them "function effectively in the changing world around them" (Taylor, Marienau, & Fiddler, 2000 as cited in Hansman & Mott, 2010, p. 15). 'For the purpose of achieving some personal sense of fulfillment, for bringing about improvement in their lives'" (Mott, 2000 as cited in Hansman & Mott, 2010, p. 15).

Purpose of Study

The purpose of this research is to develop a grounded theory, informed by the perspectives and beliefs of the students, about how to effectively implement an OPREP to increase student achievement. This study provides a detailed example of an effective implementation of an online preparation and rigorous enhancement platform (OPREP) – consistently producing high passing rates – and explore the students' experiences in this learning environment. Through the qualitative analysis of student experiences, significant commonalities and difference were isolated. Quantitatively, student performance data will be analyzed to determine early indicators on OPREP to identify Developmental Mathematics students who can benefit from intervention to improve student achievement.

WebAssign is an OPREP developed by Aaron Titus (North Carolina State University) and Larry Martin (North Park University); it has been commercially available since January 1998. It streamlines the grading process by grading the assignments for instructors and providing students with instant feedback on their answers (correct or incorrect). Students have access to learning tools/resources, (Read It, Watch It, Practice It, Master It, and Practice Another Version) and WebAssign features (Grades, Personal Study Plan, Assignment Extensions, Announcements, Calendar, Resources, Notifications). Learning tools are defined as functionalities existing within OPREP assignments; they differ from OPREP features because OPREP features exist outside OPREP assignments. This study will focus on the following research questions.

Research Questions

1. What online preparation and rigorous enhancement platform (OPREP) features did students find most useful? Why? How often did they use these features?
2. What OPREP learning tools did students find most useful? Why? How often did they use these learning tools?
3. Is there a statistically significant difference in the students' grades on OPREP assignments between students who pass the course and students who fail the course?
4. Can students' grades on different types of OPREP assignments be used as a predictor for student achievement?

CHAPTER II
LITERATURE REVIEW

This literature review provides the context and the need for a study about effectively implementing an online homework and testing management system in developmental mathematics. The first section discusses the scope of the national remedial mathematics problem, including how mathematics departments and college administrations are turning to an online preparation and rigorous enhancement platform (OPREP) to combat low passing rates. The second section summarizes the U.S. Department of Education's perspective on incorporating technology into the curriculum. It is followed by statements on incorporating technology into a mathematics course by the National Council of Teachers of Mathematics (NCTM) and national perspectives about incorporating an OPREP from the American Mathematical Society survey. Details in the ensuing section address quantitative and qualitative studies comparing web-based to paper-based homework. The subsequent section talks about the importance of one-to-one feedback for student OPREP users. The literature review ends with a description of the conceptual framework for the study, followed by the qualitative approach, Grounded Theory, and the theoretical lens, i.e., Adult Learning Theory.

Improving Developmental Mathematics Passing Rates through Online Technology

Poor passing rates in developmental mathematics have plagued educational institutions (especially community colleges) in the United States for years and the need for pedagogical change is evident. Merseth (2011) noted that 60 % of students taking a mathematics placement examination need at least one remedial course. The developmental mathematics path may have 3-5 courses. With more than 1100 institutions, community colleges account for over 44 % of higher education students (p. 2). According to McGowen (2006), as of the fall 2000 semester, 12% of the mathematics classes at four-year colleges and 57% at two-year colleges were remedial courses. Enrollment in developmental mathematics courses has increased by 73% since 1980 (Brewer, 2009). Hoyt and Sorensen (2001), report that in many institutions 30-90% of all incoming freshmen need mathematical remediation. These remedial courses are the gatekeepers to higher education and repeated failure to succeed in courses like elementary algebra often result in stagnant students who give-up on their education or burn through their financial aid in vain.

In the United States, students taking college algebra earn a grade of “D”, “W” or “F” at an alarming rate. The DWF rate is between 40-50% and in some populations has been reported as 90% (Benford & Gess-Newsome, 2006; Herriott, 2006). Brewer (2006) stated,

> Large-scale efforts to reform college algebra may not be possible in universities and colleges that base their programs on certain theoretical and practical considerations. Therefore, efforts to solve the problem of helping students succeed need to focus on interventions that can be implemented within the framework of existing programs. (p. 3)

One such intervention is revamping existing curricula by using online homework and testing management systems. With the potential to reach students throughout the country, this is a growing trend among college administrators. Currently the implementation of online preparation and rigorous enhancement platforms (OPREPs) are part of the strategy for addressing this crisis. These include institution-developed software (e.g., Virginia Tech’s Mathematics Emporium), freely available systems (e.g., WeBWorK, DRILL), commercial products (e.g., WebAssign, MapleTA, MyMathLab) and adaptive learning systems (e.g., ALEKS, HAWKES).

An OPREP typically has the following characteristics or functionality. OPREPs require students to log in to a website to access their assignments and enter their answers. The systems typically have different question types (e.g., numerical, multiple choice, fill in the blank, multiple select) and accept numerical answers as well as algebraic expressions. Instructors can typically choose questions (or pools of questions) from question banks, which may be associated with textbooks. Algorithmically generated questions can individualize assignments by providing similar questions with that same level of difficulty but different numbers. Some OPREPs allow instructors to control the number of submissions permitted per question as well as the students' access to feedback (i.e., answer key, solution key) and learning tools (e.g., electronic textbook, video lectures, step by step tutorials). Though many institutions are incorporating an OPREP, the American Mathematical Society's (AMS) report on their 2009 Homework Software Survey shows the lack of consensus about the extent and nature of technology's role in the curriculum.

Incorporating Technology in Mathematics Courses

U.S. Department of Education's perspective on technology. On February 14, 2013, James Shelton—the Assistant Deputy Secretary for Innovation and Improvement for U.S. Department of Education—testified before the U.S. House of Representatives' Committee on Education and Workforce. Shelton's (2013) testimony, *Raising the Bar: How Education Innovation Can Improve Student Achievement,* focused on:

> First, the potential of technology to fundamentally transform education, dramatically altering the levels and pace at which we develop America's human capital – our people. And second, the vital role of technology in ensuring our international leadership and affirming America's global standing educationally and economically for future generations. (p. 1)

Shelton emphasized the need to effectively implement the (recently affordable) technological solutions to address the inadequacies and failures of our current educational system.

Shelton provided examples to Congress of instructors and administrators effectively leveraging educational technology.

> Mooresville Graded School District in North Carolina—which provides a laptop for every 4th through 12th grade student using primarily digital curricular materials—uses technology as a catalyst to make learning more interesting, build better relationships among students, teachers and parents, and ultimately improve student and school performance on almost every metric. The district—one of the lowest funded districts in the state—has become the second highest performing district in the state, with graduation rates over 90 percent and millions of dollars per year in new college scholarships. (Shelton, 2013, p. 6)

The Mooresville Graded School District refers to this approach as the Digital Conversation Initiative and used the access to the Internet and multimedia tools through to supplement information presented by the teacher or textbook. Their conversation Digital Conversation Initiative extends to all their courses, not just mathematics course. This example is promising but yields little detail about effectively implementing OPREP in mathematics (specifically developmental).

Shelton (2013) emphasizes that "real transformation does not come from replicating old processes using new technology. Real innovation emerges when technology is leveraged to change and improve products or processes in ways that were impossible or impractical without the technology" (p. 4). These sentiments were echoed and extended in statements about technology in mathematics education by the National Council of Teachers of Mathematics (NCTM). NCTM states that teacher education and professional development programs must train practitioners to develop "mathematics lessons that take advantage of technology-rich environments and the integration of digital tools in daily instruction, instilling an appreciation for the power of technology and its potential impact on students' understanding and use of mathematics" (Krehbiel, 2011, p. 2).

National Council of Teachers of Mathematics' perspective. The National Council of Teachers of Mathematics (NCTM) places the onus on teachers and the school administration to strategically use technology. "Simply having access to technology is not sufficient…Teachers and curriculum developers must be knowledgeable decision makers, skilled in determining when and how technology can enhance students' learning appropriately and effectively" (Krehbiel, 2011, p. 1). Well-informed decision making and providing the proper infrastructure (and by extension utility of that infrastructure) maximizes the effective use of the technology available. NCTM declare it was the responsibility of the mathematics program and school to ensure that their students and teachers have access to and adequate training mathematics for instructional technology. According to NCTM, "effective teachers optimize the potential of technology to develop students' understanding, stimulate their interest, and increase their proficiency in mathematics" (Krehbiel, 2011, p. 1). The question becomes, how does an instructor or Mathematics Department optimize an OPREP and properly leverage it to increase student learning?

Online Preparation and Rigorous Enhancement Platform

American Mathematical Society's (AMS) homework software survey. Though many institutions are incorporating OPREP, the AMS report on their 2009 Homework Software Survey shows a lack of consensus about the extent and nature of technology's role in the curriculum. The AMS' 2009 Homework Software Survey assesses the experiences of departments using homework software, and explains the concerns of departments that were considering such software. Of the 467 responding departments (out of 1230 surveyed), 260 departments had used such software and 98 departments identified themselves as ‘disinterested’. Current users were more positive about the benefits of homework software than prospective users and much less concerned about drawbacks than prospective users. The primary benefit of using the systems was better student learning; the primary drawback being students were not showing their work.

According to the AMS Homework Survey initial faculty resistance to using homework software occurred in most departments. Shelton (2013) wrote, “Longstanding skepticism of technology in education, combined with inadequate training and support, has also thwarted the widespread adoption and use of education technology” (p. 9). Students and non-tenure-track faculty were more receptive to the software than tenured/tenure-track faculty. This commentary about student receptiveness comes from the perspective of the faculty. “This survey did not solicit information about studies measuring the effectiveness of homework software. For example, questions about the benefits and drawbacks of homework software are answered solely in terms of faculty’s beliefs (for prospective users) and observations (for current users)” (AMS Notices, 2009, p.754-760). Two apparent gaps in the research arise from not examining the students’ experiences using OPREP, and the lack of information about effective detailed and institution specific implementation strategies.

Web-based versus paper-based homework. In the last decade, several mathematics and science scholars conducted studies comparing “web-based versus paper-based homework” with inconsistent results (Clarke, 2011, p. 85). Allain and Williams (2006), used WebAssign in introductory astronomy, and concluded that there were no significant differences in conceptual understanding or test scores. Several authors— Bonham, Beichner, and Deardorff (2001), Brewer (2009), Hauk, Powers and Segalla (2015) and Demirci (2010)— concur with the generalization that there is no statistically significant difference. LaRose (2010) found that students' who use homework on-line do no worse in a course than those with pencil-and-paper homework, and in some cases may do better. In contrast, Moosavi (2009) said,

> Regardless of whether achievement is measured in terms of a single semester test, comprehensive final exam, course average, or test performance across the semester the results presented here indicate that students perform better in traditional classes than in CAI (computer aided instruction) classes regardless of the CAI curriculum used. (p. ii)

Moosavi used two OPREPs, which he referred to as Thinkwell CAI and MyMathLab CAI. These comparative studies are detailed in the following three subsections.

Students in OPREP sections perform better than those in traditional sections. Hirsch and Weibel (2003) compared approximately 1175 calculus students at Rutgers University in fall 2001. Two thirds of the sections adopted WeBWorK, the remaining third was unable to use WeBWorK due to software limitations. WeBWorK is an OPREP developed at the University of Rochester by mathematics Professors, Arnold Pizer and Michael Gage in 1995. The students in traditional sections were used as a control group. All Calculus students were required to submit paper-based homework. In the WeBWorK sections, 11 problems that were assigned to study groups in the paper-based section were replaced with assignments on WeBWorK. Hirsch and Weibel found small but significant differences in the performances of the two groups on the final examination. One realization is that many students did not attempt the homework problems assigned on WeBWorK. They found if they eliminated students who were assigned WeBWorK problems, but attempted fewer than half the problems, the WeBWorK sections did a half letter better than the control group. The average grade rose from C+ to B. The students in WeBWorK sections who did not attempt half the problems averaged no more than a C. Moreover, Hirsch and Weibel found a strong correlation between WeBWorK scores and the final examination for freshman (over 50 % of the population) and no correlation for multiple repeaters (7 % of the population).

LaRose (2010) found “that students working on homework on-line appear to do no worse in the course than those with pencil-and-paper homework, and may do better” (p. 664). The LaRose study used data from 665 students enrolled in calculus II at the University of Michigan in fall 2007. There were 24 sections with approximately 30 students each. These sections were randomly selected and divided into three groups of eight sections corresponding to type of homework given and whether the homework was graded and included in a student’s overall grade (5%). The pencil-and-paper homework group consisted of 225 students; the instructors encouraged students to complete their individual homework assignment but it was not collected nor graded. Online homework was used in the two remaining groups through WeBWorK. Like other OPREPs, WeBWorK provided the students with immediate feedback on the correctness of their answers. Instructors in the online homework groups assigned an online version of the same problems assigned by instructors in the pencil-and-paper homework group. The OPREP sections were subdivided into two groups based on if their WeBWorK homework assignments counted towards their overall grade. When using departmental examinations as measure of effectiveness, LaRose found that both groups using WeBWorK performed better than the pencil-and-paper homework group. The WeBWorK group where the homework was not graded performed statistically significantly better than the pencil-and-paper group on the second of three examinations. The statistically significance difference in examination scores was not consistent across exams or between groups.

Students in traditional sections perform better than those in OPREP sections. In contrast, Moosavi (2009) concluded that students perform better in traditional classes than in CAI (computer aided instruction). Moosavi's study used data from 688 students enrolled in a precalculus course in a public university located in Alabama in 2002. The students attended class three times a week (Monday, Wednesday and Friday) for 50 minutes or twice a week (Tuesday and Thursday) for 75 minutes. His study used an ex-post-facto design, the students were not randomly assigned to a precalculus section; however, students were unaware of the instructional method during registration. There were two different instructional methods, traditional and CAI. The CAI treatment was subdivided into two categories based on the OPREP being used, Thinkwell CAI and MyMathLab CAI. Moosavi reported that Thinkwell is designed to appeal to students with a preference for visual learning styles, while MyMathLab is designed to provide students with a self-paced interactive experience. There was no mention of instructors in the CAI precalculus sections. The students in the Thinkwell CAI sections were required to attend class in a computer laboratory and their attendance was a part of their final grade. The researcher used two exams that were consistent across all students as well their final course grade as dependent variables representing student achievement. Moosavi found that students receiving traditional instructions perform better than those who received Thinkwell CAI or MyMathLab CAI.

No significant difference when students use an OPREP. Bonham, Beichner, and Deardorff (2001) compared students using WebAssign to students with paper-based homework for two semesters at North Carolina State University. The first semester consisted of students enrolled in large sections, approximately 110 students, of a calculus-based physics course; however, the second semester students were enrolled in smaller sections, approximately 60 students, of algebra-based physics course. The instructor, class meeting days, lecture and assignment were consistent across sections. After comparing homework, quiz and examination grades, Bonham et al. found that the method of collecting and grading homework made very little difference in student performance. The WebAssign sections had higher test and homework averages but differences were not statistically significant. Bonham and colleagues cited differences in the student's ability (higher GPA and SAT scores) as a possible reason for higher averages in the WebAssign sections. The researchers noted that the underlying pedagogy is the critical issue in effective learning, while technology itself does not improve or harm student learning.

Demirci (2010) compared 168 students enrolled in an Introductory Physics course in Balıkesir University (Turkey) over two semesters from fall 2005 (Physics 1) to spring 2006 (Physics 2). The web-based homework used was called "online testing"; it is unclear if it was an institution developed OPREP. The Web-based homework system that Demirci used was developed by Linux based php extension html environment using the MySQL database system and had two main modules. A two-group, pretest–posttest quasi-experimental design was used with standardized test scores representing student achievement. The instruments included the Force Concept Inventory and Conceptual Survey of Electricity and Magnetism. There were no significant differences in the performance on the standardized test between the paper-based homework group and the web-based group.

Hauk, Powers and Segalla (2015) compared 439 students enrolled in 19 moderately sized college algebra courses at a large public university in the United States. WeBWorK was used by 12 sections and the remaining seven sections had paper-based homework. Four of the 15 instructors were Graduate Teaching Assistants and they lacked teaching experience. The majority of instructors (14 out of 15) made homework count for 5-15 % of the overall grade. Student achievement was measured by a 25-item, multiple-choice, paper-based examination with established face and content validity as well as a Cronbach alpha reliability of 0.82. This examination was used as pre- and post-test. Hauk et al. reported that a comparison of mean post-test scores by homework group (web-or paper-based), controlling for pre-test score, indicated a slightly higher gain for the web-based group, however the difference was not statistically significant.

College algebra student perceptions of WeBWorK. Hauk and Segalla (2005) surveyed 11 instructors and 358 students enrolled in 12 moderately sized college algebra courses about their perceptions of WeBWorK. The seven-item student survey was designed to measure their comfort with and their views on WeBWorK. It contained six Likert scale questions with five choices and one open response question that asked the students to comment about WeBWorK. The instructors were interviewed and received a similar survey. The researchers used the qualitative constant-comparative coding methods to analyze data. Students felt that accessing the Internet was fairly easy and they were pretty comfortable using a computer. They felt that they studied about the same as they would with paper-based homework. It should be noted that students received instant feedback in terms of correctness and had the ability to contact their instructor through WeBWorK. There was no mention of additional learning tools available on WeBWorK such as lecture videos or step-by-step interactive tutorials. Students expressed concerns about some of the system's idiosyncrasies, such as not recognizing a correct answer because it was incorrectly formatted due to difficulty with the interface. Some said "It took longer to input [an] answer than the time it took to actually solve the problem". Ten percent of students also mentioned the urge to 'put off homework because it's so frustrating' to use WebWork" (Hauk et al., 2005, p.240).

The students' opinions about the OPREP were influenced by their instructor's perspectives of its usefulness as an educational tool. All instructors were of the opinion that the system saved time because grading was automated. Three instructors saw little positive value in web-based homework and the majority of their students hated WeBWorK, and thought it was useless or a waste of time. Four instructors saw value in the system but had reservations based limited feedback (correct or incorrect) provided by WeBWorK. The majority of their students reflected these sentiments by commenting positively on WeBWorK helpfulness but preferring the detailed feedback received from their instructor. The remaining four instructors felt that WeBWorK was a valuable tool and their students shared their opinion. These students suggested changes to the system that would improve their interaction.

Instructors' opinions were also reflected in their student performance in terms of their improvement from the pre-test to post-test. Students whose instructors thought that WeBWorK was a value tool had larger increases in their learning than those with instructors who were less favorable. The highest increases were achieved by students of instructors whose opinion fell in the useful, but with reservations group. The highest pre- to post-test gains occurred when the instructor recognized what the WeBWorK tool could be used for and provided supplemental feedback (e.g., comments on mildly non-routine problems in from a paper-and-pencil homework assignment) when intervention was deemed necessary. Hauk et al. (2005) wrote, "Results support the conjecture that even a narrow use of WeBWorK, as a substitute for handwritten homework, is at least as effective as traditionally graded paper and pencil homework for student learning in college algebra" (p. 229).

Improvement in mathematics self-efficacy and achievement not significantly different. Brewer (2009) compared 145 students enrolled in a College Algebra course in Salt Lake Community College during the fall 2008 semester. There 65 students in the web-based homework group and 80 in the control group. He did not provide the name of the OPREP but by his description of it is similar to MyMathLab. There were four sections using the OPREP who functioned as the treatment group. The five sections that used traditional pencil-and-paper homework (referred to as textbook homework) were the control group. Brewer used a quasi-experimental, posttest design that was intended to determine if significant difference in mathematical achievement, measured by a departmental final examination, existed between the groups. The OPREP group generally had higher final examination scores but they were not significantly different than the pencil-and-paper homework group.

Brewer also compared the OPREP's effect on the students' mathematics self-efficacy, measured by the Mathematics Self-Efficacy Scale, using a pretest-posttest design. There was significant improvement in mathematics self-efficacy in the treatment and control group when compared to the beginning of the semester; however, the increase in mathematics self-efficacy in the OPREP group was not significantly different than the pencil-and-paper homework group. Brewer suggested that an OPREP may be more beneficial to students with inadequate prerequisite mathematics ability or multiple repeaters. Among other results, the author reported that more students with low incoming skill levels and more repeating students received a passing grade when using online homework than did their higher-skilled, first-time counterparts, although the differences were not significant. Brewer (2009) concluded, "it appears as if online homework is just as effective as textbook homework in helping students learn college algebra and in improving students' mathematics self-efficacy" (p. iv).

Impact of OPREP on student learning and strategies. Hodge, Richardson and York (2009) surveyed 1333 college algebra students who used the web-based homework system, iLrn, focusing on their motivations and perceptions on learning related to the OPREP. They used the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991), which is based on a general cognitive view of motivation and learning strategies. The MSLQ framework embraces self-efficacy, value and emotional response of student to the task. Multiple regression and correlation were used to analyze student perspectives of the factors that influenced their mathematical learning. The dependent variable was students' perception that using the web-based homework would increase their mathematical understanding more than traditional paper/pencil methods. The potential predictors/ independent variables are expected course grade, previous use of an OPREP in mathematics, ease of navigation of the OPREP, frequency with which homework was completed, and demographic variables. The only significant predictors were expected course grade (grade = B), previous use of an OPREP, students were motivated to complete more homework when using the OPREP, and the ease of navigating the OPREP. This model accounted for 47% of the variance in the increased mathematics understanding from using the OPREP. The partial correlation coefficients showed two major effectors: 1) that students were motivated to complete more homework when using the OPREP, and 2) the importance of the ease of navigating the OPREP; they accounted for 13% and 5% of the variance, respectively.

Hodge et al. (2009) used *Peer Learning* and *Help Seeking* subscales to assess learning strategies and the *Control of Learning Beliefs* expectancy scale, assessing motivation, to compare student responses. Correlation analysis was used to determine if a relationship existed between the students' scores of these subscales as well as their motivation to complete more homework using web-based homework. The *Peer Learning* and *Help Seeking* subscales had a significant strong positive correlation of 0.54 as they both measure learning strategies. All three subscales had significant positive correlations with “student motivation to complete more homework using web-based homework”; however, the correlation coefficients were small ranging from 0.09 to 0.23. The highest correlation, 0.23, of the three subscales was the *Control of Learning Beliefs* expectancy scale and the lowest was the *Peer Learning* subscale. The *Help Seeking* subscale had a correlation of 0.13 with “student motivation to complete more homework using web-based homework”. Hodge concluded, “The results suggest that students were motivated to complete more homework using the web-based tool than with traditional paper-based methods” (p. 618). Approximately one-third of the students felt that OPREP increased their mathematical understanding more than they would learn with paper-based homework. According to Hodge, “students who felt more motivated to complete their homework using the web-based system ‘were also more likely to acknowledge the need for help and seek out assistance from others’” (p. 618).

The majority of the reviewed studies compared control group versus treatment (required to use an OPREP) group to measure effect of using an OPREP on student achievement or student beliefs. An apparent gap in the research is the lack of detailed and institution-specific implementation strategies, and this gap leaves many question unaddressed. The students in the treatment group were required to do homework online, but it is of interest to know further if results would differ if the implementation strategy differed? Were students given an introductory assignment to teach them how to enter different answer types in order to mitigate potential frustration and minimize problems concerning input format errors? Was there a brief introduction to navigating the system in order to point out resources and promote optimal use?

Were students given weekly deadlines on the homework assignments or were students required to complete all the assignments before the end of the semester? Did an instructor encourage or even check if the students were keeping pace with the hard or soft deadlines? Were students provided opportunities to request an extension after the deadline? Did the department use the OPREP for other types of assignments such as OPREP in-class assignments, OPREP quizzes or OPREP practice examinations? If so, were these different type of assignments (e.g., OPREP quiz inside or outside of the classroom) required? Did the department use the OPREP to provide the students with additional resources such as power point lectures? In addition to the immediate feedback in terms of correctness, did the student have access to additional feedback such as video lectures, step-to-step interactive tutorials and solution keys when applicable? Can the format, delivery and use of the online homework and testing management system make a difference?

One-on-one tutoring/ feedback. Benjamin Bloom (1984) discussed the two-sigma problem, in which students in a traditional classroom were outperformed by two standard deviations when compared to students who received one-on-one tutoring. Shelton (2013) provides further insight by noting that a student in the 50th percentile would instead be in the 98th percentile and provides further evidence that we have been unable to close the gap between the traditional classroom and the individualized instruction that might solve the two-sigma problem. More particularly, Shelton notes “Our challenge is to find a way to affordably provide each child this opportunity” (p. 4). With advent of affordable OPREP and Internet access, the question becomes can OPREP be leveraged to replicate this individualized instruction so instructors can tackle Bloom’s two-sigma problem?

With individualized instruction, a student receives immediate feedback from their instructor and can incorporate that feedback when attempting future questions. In a traditional class, this one-on-one feedback is hampered because instructors have to be economical with their time management due to the need to pay attention to all other students. Zerr (2007) emphasized the importance of the teacher's immediate feedback in the traditional classroom on student engagement (measured by higher levels of participation when retrying questions) and success (measured by performance on assessments). "Such an attempt-feedback-reattempt sequence of events is arguably a crucial aspect of gaining a thorough understanding of a given topic. Unfortunately, this type of student-instructor interaction is not always present outside of class when students are working on traditional pencil-and-paper homework assignments" (p.56). Zerr used a mixed method approach to analyze the effects of an OPREP on mathematics achievement of 27 calculus I students. He found that students who completed a higher percentage of their online homework assignments achieved higher examination and quiz grades.

Zerr (2007) recognized learning management systems (i.e., Blackboard, Angel, WebCT) as well as OPREPs could provide the attempt-feedback-reattempt sequence outside the classroom. Suppose Jane Doe attempts to work through a possible solution for a homework question on OPREP assignment. Once she submits her answer the OPREP provides immediate feedback in the form of correct or incorrect. If she answers incorrectly, the system provides learning tools in the form of lecture videos, electronic textbooks and step-by-step tutorials that she can use to guide her to a correct solution. If she chooses the lecture video she can fast forward to relevant portions or rewind when she needs the instructor to repeat a statement. Jane can pause the video to apply what she absorbed in the context of her question. When she is ready she reattempts the homework question and submits her revamped answer on the OPREP.

This attempt-feedback-reattempt sequence can take many forms, and involve several learning tools when the student deems it necessary. Brewer (2006) wrote, “Theories of learning, such as constructivism (Davis, Maher, & Noddings, 1990) and social cognitive theory (Schunk, Pintrich, & Meece, 2008), state that student practice needs to be followed by instructor feedback in order for students to verify their understanding” (p. 3).

Even though several OPREPs could replicate Zerr’s attempt-feedback-reattempt sequence, inconsistent results among investigators that use the same system still persist. Hauk and Sequalla (2015) and Hirsch (2003) reported contradicting results when using WeBWorK (supported by the MAA and the NSF) to measure the effectiveness of online homework assignments. Each study compared a traditional section to a section using WeBWorK; however, Hirch (2003) reported that students in the WeBWorK section achieved on average, final examination grades that were 4% higher than their peers in the non-WeBWorK sections. Hauk (2005) found no statically significant difference. Zerr (2007) remarked that in both of these studies, when a student answered a question, they were only told if they were correct or incorrect making it difficult to adjust behavior because no detailed feedback was provided to students answering questions incorrectly. In response to this situation, Zerr developed his own system using Blackboard and provided detailed solutions as a part of the feedback. His results were statistically significant. Thus, we are led to ask: Does the type of feedback provided by OPREP have an impact on its effectiveness?

Previous quantitative studies were comparative in nature with a traditional classroom control group versus a treatment group using an OPREP. As cited above, the results from various studies were inconsistent and sometimes contradictory; ranging from no statistically significant results to a possibly positive effect or negative impact on student achievement. The

AMS' qualitative survey study of Mathematic Departments (Kehoe, 2009) is of interest, because it did not solicit information about studies measuring the effectiveness of homework software. For example, questions about the benefits and drawbacks of homework software are answered solely in terms of faculty's beliefs (for prospective users) and observations (for current users). Two apparent gaps in the research arise from not examining the students' experiences using OPREP (in terms of their preferred OPREP functionality), and the lack of information about effective detailed and institution specific implementation strategies.

Conceptual Framework

Grounded Theory. One promising avenue to understanding the student experiences is a qualitative method called grounded theory, where the central phenomenon of the student experience is grounded in the data and revealed through triangulation of several data sources. Grounded theory uses the viewpoints of the participants (in this case, anonymous students) to develop theory about a process or action. In 1967, systematic grounded theory was introduced by Glaser and Strauss. They introduced the method as a contrast to a priori theoretical orientations in sociology. Glaser and Strauss "held that theories should be 'grounded' in data from the field, especially in the actions, interactions, and social processes of people" (Miller & Salkind, 2002, p. 152). Strauss' systematic approach to grounded theory is stringent because it consists of prescribed categories when coding data. This study will use Charmaz's (2005) constructivist approach to grounded theory because it affords more flexibility during open coding, axial coding and selective coding phases of analysis. Grounded theory is both a qualitative approach and a method of data analysis so the implications will be grounded in the students' experiences.

Adult Learning Theory. The researcher is using a social constructivism framework with a philosophical/ theoretical lens of adult learning theory. Merriam (2001) states,

> The central question of how adults learn has occupied the attention of scholars and practitioners since the founding of adult education as a professional field of practice in the 1920s. Some eighty years later, we have no single answer, no one theory or model of adult learning that explains all that we know about adult learners. (p. 3)

In the 1970's, Malcom Knowles — a theorist and practitioner of adult education – is credited with pioneering andragogy as model and theory. Knowles defined Andragogy as "the art and science of helping adults learn" (Fidishun 2000). Knowles suggested the principles of andragogy in 1984:

> Adults need to be involved in the planning and evaluation of their instruction.
> Experience (including mistakes) provides the basis for the learning activities. Adults are most interested in learning subjects that have immediate relevance and impact to their job or personal life. Adult learning is problem-centered rather than content-oriented.
> (Kearsley, 2010)

From 1980 through 1990, Knowles provided six assumptions (self-concept, adult learner experience, readiness to learn, orientation to learning, motivation to learn and the need to know) about the characteristics of adult learners. The six assumptions were listed in the 4th edition of the *Adult Learner: A Neglected Species*.

The participants in this study were required to know and demonstrate mastery of the concepts of elementary algebra to satisfy one educational requirement. Developmental courses (e.g., elementary algebra) are the gatekeepers to higher education and slow progression through these courses can adversely affect graduation rates. Earning a college degree has immense implications for an individual's employment opportunities and quality of life. Many students recognize that their education is a vehicle to change their lives. This realization facilitates the experience of a tangible need to complete their coursework including their developmental mathematics requirements. Adult students become ready to learn when "they experience a need to learn in order to cope more satisfyingly with real-life tasks or problems" (Knowles, 1980 p 44, as cited in Fidishun, 2000). Given that participants need to learn; the lens of andragogy focused on self-directed learning that was facilitated through the incorporation of an OPREP in their class. "In its broadest meaning, 'self-directed learning' describes a process by which individuals take the initiative, with or without the assistance of others, in diagnosing their learning needs, formulating learning goals, identify human and material resources for learning, choosing and implement appropriate learning strategies, and evaluating learning outcomes" (Knowles, 1975, p. 18).

Summary

Due to the autonomy an instructor exercises in the classroom, the vast spectrum of their opinions about educational technology, and the continual education that faculty need to effectively use the technology, more relevant research is necessary. An apparent gap in the research arise from not examining the students' experiences using an OPREP in terms of how the students interact with the available features and learning tools as well their impact on student learning. The existing research focuses on the impact of OPREP homework assignments but this is just one of several categories OPREP assignment that impact student achievement on a summative assessment. Existing research often refers to OPREPs as online homework or web-based homework systems, but this severely limits the use and thus implementation of these online homework and testing management system. OPREP quizzes, OPREP practice examinations, OPREP in-class assignments may also have an impact student achievement. Developing OPREP implementation strategies informed by student usage experiences and student performance on relevant OPREP assignments can improve effectiveness of integrating an OPREP in a mathematics course.

Building from the existing qualitative and quantitative studies, a mixed methods approach would give administrators and faculty a firm basis to make better decisions when adopting and implementing an OPREP. The desired increase in student achievement through use of an OPREP depends on mathematics instructors' implementation strategies. Online educational technology is a tool meant to enhance the students' educational experience; unfortunately, this tool is limited by how the instructor implements it as indicated in Chappell's (2011) Bill Gates interview.

> So 10 years after starting the Bill and Melinda Gates Foundation—and deciding to put billions into improving education in America—he knows that access to technology is no longer the issue. How we use that technology in the classroom, and whom we hire to teach are. (p. 83)

This study seeks to add to the literature by providing a detailed example of an effective (consistently producing relatively high passing rate) implementation of an OPREP (see Appendix A). The researcher hopes that exploring the students' experiences in this learning environment will better prepare faculty for developing or refining OPREP implementation strategies.

CHAPTER III
METHODOLOGY

This chapter describes the study's setting and participants, the types of data collected and the sources of the data, including a qualitative online questionnaire and student artifacts. The nature and purpose of the quantitative data will be presented to provide context for the generalizability of the study’s results. The criteria to pass the Elementary Algebra course will be given. A description of the OPREP, WebAssign, assignments and how the OPREP is implemented will be provided. The researcher will expound on the statistical methods used to analyze the data in order to answer the following research questions:

1. What online preparation and rigorous enhancement platform (OPREP) features did students find most useful? Why? How often did they use these features?
2. What OPREP learning tools did students find most useful? Why? How often did they use these learning tools?
3. Is there a statistically significant difference in the students’ grades on OPREP assignments between students who pass the course and students who fail the course?
4. Can students’ grades on different types of OPREP assignments be used as a predictor for student achievement?

Setting and Participants

This study focuses on adult students enrolled in an urban community college within a university system. The university enrolls 96,500 students in its community colleges. From 2009 through 2015, on average approximately 37.4% of those students were Hispanic, 28.9% Black, 17.6% White, 15.8% Asian/ Pacific Islander and 0.3% Alaska Native / Native American. Approximately 90% of the students, within the highlighted community college, have at least one developmental need and 85% are financial aid eligible. The student population in this community college consist of 42.3% male, 57.2% female, 31.9% African American/ Black, 0.2 % Alaska Native / Native American, 14.9 % Asian/ Pacific Islander, 14.9 % Caucasian / White and 38.0 % Hispanic. This urban college seeks to improve both its developmental mathematics passing rates and graduation rate of 47.4% and 15% respectively. The relevance and need to develop strategies are dire; hence the importance of this study as a direct answer to the call for innovative pedagogical techniques to increase both the developmental courses passing rate and thus the graduation rate.

Qualitative research questions: data collection and analysis. The first two research questions are qualitative in nature and utilize data collected through an online questionnaire as well as artifacts (hand written student comment sheets — from student evaluations — and online student comments) from 2009 through 2015. Through the qualitative analysis of student experiences, significant commonalities and difference were isolated.

This study explores the experiences of Developmental Mathematics students in the researcher's Elementary Algebra courses. A link to the online questionnaire — through Qualtrics — was emailed to former students and their participation was informed and voluntary. The questionnaire was specifically about students' experiences using and learning Mathematics with WebAssign (an OPREP). It included open-ended interview-type questions, Likert scale (frequency and satisfaction) questions, and demographic questions, as well as others. Descriptive statistics were calculated for the Likert scale questions. The researcher used a grounded theory approach to analyze data by using the three data points (namely the questionnaire, student evaluation and student online comments) to triangulate common themes and subthemes in the students' responses. Through several stages of coding, using Charmaz's

(2005) constructivist approach, the investigator used the data to identify the central phenomenon and generate a grounded theory about effective teaching with an OPREP. The researcher used a social constructivism framework with a philosophical/ theoretical lens of adult learning theory.

The open-ended responses about student learning were rated by three coders including the researcher. The researcher analyzed the student open-ended responses from the questionnaire and started open coding. Student evaluation comment sheets and students' online comments were used to refine the coding and make more connection in order identify the emergent themes. Once these initial themes were established, the researcher used a spreadsheet to categorized each comment in order to quantify the volume of comments under each theme. Comments were listed in the rows and emerging themes as column headings. A "1" placed under the appropriate column and adjacent to the relevant comment signaled classification. Raters could classify comments under multiple categories. While rating the responses, coders discussed the meanings of theme and refined the categories when necessary. Coders were able to create their own category if they felt a response evoked a theme not accounted for in the initial categories. If a comment expressed a theme not encompassed by the existing categories, then a coder added an additional theme. For example, two coders added a category for convenience and the researchers revisited all comments looking through this lens.

Cohen's kappa, instead of percentage agreement, was used to calculate inter-rater agreement, also known as inter-rater reliability. According to Lombard (2002), "When reliability is not established, the data and interpretations of the data can never be considered valid" (p. 589). Cohen's kappa was used as the preferred measure because it accounts for the amount of agreement that can occur by chance. Kappa was proposed by Cohen in 1960 and extended by Fleiss to include multiple raters. Cohen's kappa, 0.71, was calculated according Fleiss' (2003) specifications. The strength of agreement is considered fair to good (0.41 – 0.75) according to Fleiss and substantial agreement (0.61 – 0.80) according to Landis and Koch.

Artifacts such as the hand written student comment sheets — from hand written student evaluations — as well as online student comments – from online student evaluations and www.ratemyprofessor.com – were anonymous. The OPREP student experiences questionnaire was also anonymous for students who chose not to self-identify; however, the instrument provided demographic information from the 129 participants. Tables 1 through 5 show the ethnicity, age, gender, student status and employment status of the OPREP student experiences questionnaire participants. Hispanic (55) and Black (25) students represent a combined 62% of the population. Fifteen out of the 129 of the participants (approximately 12%) preferred to not disclose their ethnicity.

Table 3.1

Questionnaire: Self-identified ethnic origin

#	Answer		Response	%
1	I Prefer Not to Disclose		15	12%
2	Black, Afro-Caribbean, or African American		25	19%
3	East Asian or Asian American		8	6%
4	Latino or Hispanic American		55	43%
5	Middle Eastern or Arab American		2	2%
6	Native American or Alaskan Native		0	0%
7	Non-Hispanic White or Euro-American		10	8%
8	South Asian or Indian American		4	3%
9	Other		10	8%
	Total		129	100%

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The majority of the OPREP student experiences questionnaire participants (46%) are between the ages of 20 and 25.

Table 3.2

Questionnaire: Student Age range

#	Answer		Response	%
1	Under 20 years old		45	35%
2	20-25 years old		59	46%
3	25-30 years old		17	13%
4	30-35 years old		2	2%
5	35-40 years old		6	5%
6	40 years or older		0	0%
	Total		129	100%

Women represent more than half of the 116 participants that identified their gender.

Table 3.3

Questionnaire: Participant gender

#	Answer		Response	%
1	Male		50	43%
2	Female		64	55%
3	I Prefer Not to Disclose		2	2%
	Total		116	100%

Approximately 74% of the participants were enrolled as full-time students by registering for at least 12 credit hours during the semester they took Elementary Algebra.

Table 3.4

Questionnaire : Student enrollment status

#	Answer		Response	%
1	Part time student		34	26%
2	Full time student		95	74%
	Total		129	100%

In terms of employment status, 74% of the participants worked at least part-time including home care providers.

Table 3.5

Questionnaire: Participant self-identified employment status

#	Answer		Response	%
1	Part time job		52	40%
2	Full time job		41	32%
3	Home Care Provider		2	2%
4	No job		34	26%
	Total		129	100%

Quantitative research questions: data collection and analysis. The last two research questions are quantitative in nature and utilize time-series cross sectional data (panel data) from a high OPREP usage instructor, where student scores on different types of OPREP assignments are compared to the change in student achievement. Specifically, de-identified data available from previous WebAssign users are analyzed. To address question (3), a t-test determined the statistically significant differences in the students' grades on OPREP assignments (e.g., In-Class Assignments average, Homework assignments average, Practice Final examination average, Practice Midterm average, Quiz average) between students who passed the course and students who failed the course. Question (4) asked about the relationship between students' grades on OPREP assignments and student achievement (e.g., score on the Midterm examination, score on the Final examination, and score on CBT Final examination/exit examination) through correlation. A correlation matrix was used to identify the highly correlated (greater than 0.4 in absolute value) variables. Once identified, the investigator used regression to determine what category of student grades on OPREP assignments could be used as predictors for student achievement. Multiple regression data analysis was used to determine the most relevant possible independent variables (students' grades on OPREP assignments) and their ability to predict the dependent variables (student achievement measured by their performance on an exit examination). The purpose was to use the relevant predictors as early indicators on WebAssign to identify developmental mathematics students who can benefit from intervention. Important factors such as student demographics were considered when identifying possible patterns in subsets of the population.

De-identified OPREP data (grades, time and system activity) from 261 former Elementary Algebra students from 2012 through 2015 served as the raw material for this analysis. The Institutional Review Board provided demographic, socio economic and other pertinent data after de-identifying the students. Of the 253 students, 74% were eligible for financial aid as determined by their Pell grant status. For purposes of this discussion, a student with a Pell grant has a low socio economic status (LSES) as depicted in Table 6.

Table 3.6

Student's eligibility for a Pell grant (n=253) and low socio economic status (LSES)

Pell Flag	Frequency	Percent	Cumulative Frequency	Cumulative Percent
No	52	20.55	52	20.55
Unknown	13	5.14	65	25.69
Yes	188	74.31	253	100.00
Frequency Missing = 8				

LSES	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	52	21.67	52	21.67
1	188	78.33	240	100.00
Frequency Missing = 21				

For purposes of possible future generalizability, Tables 3.7 through 3.9 describe the season, years, time of day and meeting days of the 261 students included in this quantitative analysis. Students enrolled during the winter semester were excluded from the data set. Approximately, 54% of the students enrolled during a fall semester.

Table 3.7

Student enrollment by season (n=261)

Season	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Fall	140	53.64	140	53.64
Spring	109	41.76	249	95.40
Summer	12	4.60	261	100.00

Approximately 31% of the students were enrolled in this Elementary Algebra course in 2013.

Table 3.8

Student enrollment by season (n=261)

Year	Frequency	Percent	Cumulative Frequency	Cumulative Percent
2012	74	28.35	74	28.35
2013	80	30.65	154	59.00
2014	73	27.97	227	86.97
2015	34	13.03	261	100.00

The majority (56%) of the face-to-face meetings were in the early afternoon at 12 pm. Approximately 68% meet face-to-face twice a week (for two teaching hours a day); the most common meeting days were Tuesdays and Thursdays.

Table 3.9

Face-to-face meeting data (n=261)

Actual Time	Frequency	Percent	Cumulative Frequency	Cumulative Percent
10:00:00.000	57	21.84	57	21.84
12:00:00.000	145	55.56	202	77.39
14:00:00.000	59	22.61	261	100.00

Class Time	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Afternoon	204	78.16	204	78.16
Morning	57	21.84	261	100.00

Day(s)	Frequency	Percent	Cumulative Frequency	Cumulative Percent
M	13	4.98	13	4.98
MTh	19	7.28	32	12.26
TU	20	7.66	52	19.92
TUTH	171	65.52	223	85.44
TUWE	12	4.60	235	90.04
W	26	9.96	261	100.00

Tables 3.10 through 3.14 show the ethnicity, gender, age, class standing and student status of the OPREP student experiences questionnaire participants. Hispanic (111) and Black (89) students represent a combined 79% of the population. Thirteen out of the 253 (approximately 5%) of the students whose ethnicity was specified were listed as unknown.

Table 3.10

Student ethnic origin (n=253)

Ethnicity Imputed Group 1	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Asian or Pacific Islander	23	9.09	23	9.09
Black	89	35.18	112	44.27
Hispanic	111	43.87	223	88.14
Unknown	13	5.14	236	93.28
White	17	6.72	253	100.00
Frequency Missing = 8				

Women represent more than half of the 253 participants that identified their gender. Of the 261 students, 8 students have no specified gender on file.

Table 3.11

Student gender (n=253)

Gender	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Men	103	40.71	103	40.71
Women	150	59.29	253	100.00
Frequency Missing = 8				

The majority of the OPREP student experiences questionnaire participants (61%) are between the ages of 18 and 21.

Table 3.12

Distribution of student age (n=253)

Age	Frequency	Percent	Cumulative Frequency	Cumulative Percent
18	35	13.83	35	13.83
19	41	16.21	76	30.04
20	47	18.58	123	48.62
21	32	12.65	155	61.26
22	19	7.51	174	68.77
23	18	7.11	192	75.89
24	14	5.53	206	81.42
25	10	3.95	216	85.38
26	7	2.77	223	88.14
27	7	2.77	230	90.91
28	4	1.58	234	92.49
29	1	0.40	235	92.89
30	3	1.19	238	94.07
31	4	1.58	242	95.65
32	1	0.40	243	96.05
33	3	1.19	246	97.23
34	1	0.40	247	97.63
35	1	0.40	248	98.02
37	2	0.79	250	98.81
38	1	0.40	251	99.21
42	1	0.40	252	99.60
51	1	0.40	253	100.00
Frequency Missing = 8				

Approximately 76% of the students who were enrolled in this course were considered freshman according to the credits completed before the start of the semester.

Table 3.13

Student class standing (n=253)

Class Standing	Frequency	Percent	Cumulative Frequency	Cumulative Percent
FRESHMAN	193	76.28	193	76.28
SOPHOMORE	60	23.72	253	100.00
Frequency Missing = 8				

Approximately 71% of the participants were enrolled as full-time students by registering for at least 12 credit hours during the semester they took Elementary Algebra.

Table 3.14

Student enrollment status (n=126)

Full Part Type Desc	Frequency	Percent	Cumulative Frequency	Cumulative Percent
FULL-TIME	89	70.63	89	70.63
PART-TIME	37	29.37	126	100.00
Frequency Missing = 135				

Criteria for Passing the Course

Students were placed into Elementary Algebra if they scored less than 40 on the American College Testing Program's (ACT) Algebra Compass entrance placement examination. The distribution of the ACT Algebra Compass entrance examination scores is depicted in Table 3.15. The mean and standard deviation on the ACT Algebra Compass of the students was 22 and 6 respectively.

Table 3.15

Distribution of the students on the computer-based ACT Algebra Compass entrance examination scores

AlgCompassEntrance	Frequency	Percent	Cumulative Frequency	Cumulative Percent
15	26	10.92	26	10.92
16	30	12.61	56	23.53
17	25	10.50	81	34.03
18	20	8.40	101	42.44
19	13	5.46	114	47.90
20	12	5.04	126	52.94
21	8	3.36	134	56.30
22	12	5.04	146	61.34
23	10	4.20	156	65.55
24	7	2.94	163	68.49
25	9	3.78	172	72.27
26	7	2.94	179	75.21
27	7	2.94	186	78.15
28	12	5.04	198	83.19
29	6	2.52	204	85.71
30	6	2.52	210	88.24
31	3	1.26	213	89.50
32	5	2.10	218	91.60
33	7	2.94	225	94.54
34	2	0.84	227	95.38
35	1	0.42	228	95.80
36	1	0.42	229	96.22
37	6	2.52	235	98.74
38	3	1.26	238	100.00
Frequency Missing = 23				

In order to pass this Elementary Algebra course, students must pass a comprehensive Computer-Based Test (CBT) final examination administered and scored by the college's testing department as an exit examination. The comprehensive CBT exit examination (35% of the student's final grade) consists of 25 equally weighted multiple-choice questions (with distractors) worth four points each. Students without special accommodations have 100 minutes to attempt to achieve a 60% (15/25) or higher in order to pass the examination. A university-wide committee of staff and faculty members, including mathematics subject matter experts, created the CBT exit examination. In addition to the CBT exit examination, the Mathematics Department also requires each instructor of an Elementary Algebra section to administer a paper-delivered departmental final examination before the CBT exit examination. This paper-delivered test (PDT) consists of 10 multiple-choice questions and 12 short-answer questions. The comprehensive departmental final examination, created by the department's Developmental Mathematics committee, is graded by the section instructor and counts for 5% of the student's final grade. It is important to note that the aforementioned departmental final examination is not the CBT final examination. Only the CBT final examination functions as an exit examination; its delivery, grading, administration and weight, in terms of the cumulative average, differ from the PDT departmental final examination.

Of the 261 students who completed the course, 80 % (208/ 261) passed and 20 % (53/261) of the students failed the course. The highest score was 100 and the lowest score was 20. The distribution of CBT final examination scores is depicted in Table 3.16. The mean and standard deviation on the CBT Final examination was 74 and 19 respectively. The mode was 92 and approximately 50% of the scores were between 60 and 88.

Table 3.16

Distribution of the CBT Final examination scores

CBT Final Exam	Frequency	Percent	Cumulative Frequency	Cumulative Percent
20	2	0.77	2	0.77
24	1	0.38	3	1.15
28	1	0.38	4	1.53
32	3	1.15	7	2.68
36	7	2.68	14	5.36
40	6	2.30	20	7.66
44	3	1.15	23	8.81
48	7	2.68	30	11.49
52	11	4.21	41	15.71
56	12	4.60	53	20.31
60	15	5.75	68	26.05
64	22	8.43	90	34.48
68	11	4.21	101	38.70
72	16	6.13	117	44.83
76	18	6.90	135	51.72
80	22	8.43	157	60.15
84	21	8.05	178	68.20
88	21	8.05	199	76.25
92	29	11.11	228	87.36
96	21	8.05	249	95.40
100	12	4.60	261	100.00

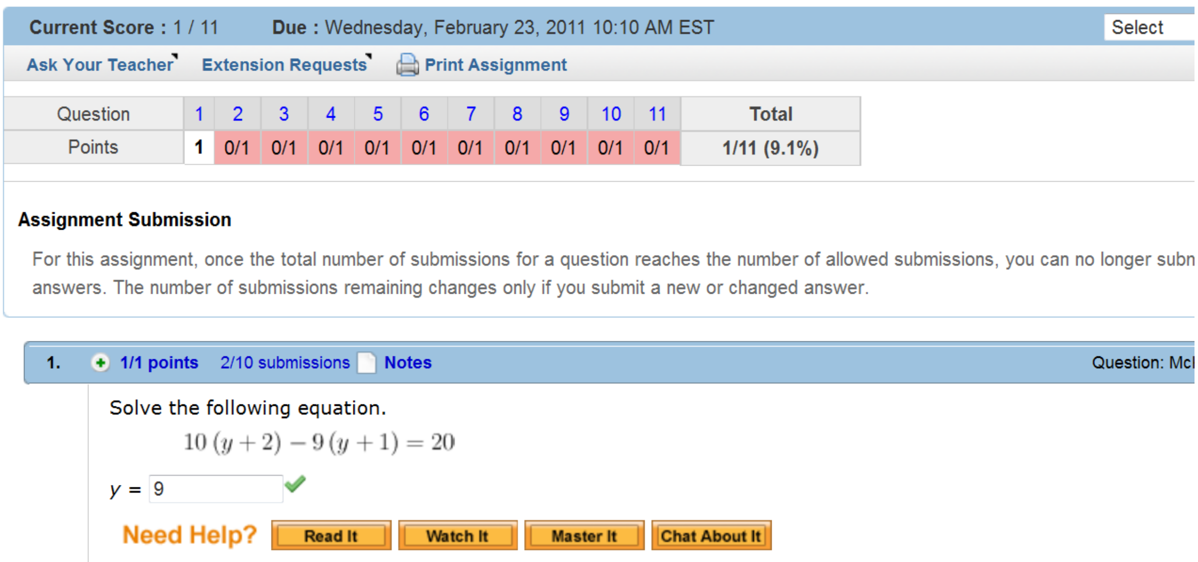
CBT Exit Exam Status	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Fail	53	20.31	53	20.31
Pass	208	79.69	261	100.00

OPREP/WebAssign Assignments

WebAssign is an OPREP developed by Aaron Titus (North Carolina State University) and Larry Martin (North Park University); it has been commercially available since January 1998. It streamlines the grading process by grading the assignments for instructors and providing students with instant feedback (correct or incorrect) on their answer submissions as depicted in Figure 3.1.

Figure 3.1

Example of OPREP/WebAssign instant feedback (correctness)



Students have access to the relevant sections of their electronic textbook (e-book) immediately and they are afforded a 14 to 21-day grace period before they are required to purchase access. The e-book used was Elementary Algebra 9th edition by Patrick McKeague. Figure 3.2 depicts some of the learning tools resources (i.e., Read It, Watch It, Practice It, Master It, and Practice Another Version) that students can access within most assignments.

Figure 3.2

OPREP/WebAssign learning tools

All questions on OPREP Homework assignments and In-Class assignments offer some combination of learning tools.

The OPREP Homework assignments and In-Class assignments share the following characteristics. Each student is typically allowed 7-10 submissions per question. One exception is multiple-choice questions. For example, given a multiple choice question with five answer choices students receive a 20% deduction on each submission after the first, to deter guessing and gaming the system. Recall that each student has the same type of question with a similar level of difficulty; however, the order of the problems and numbers in each problem are different. The numbers are algorithmically generated. Students submit one question at a time and receive immediate feedback (e.g., correct or incorrect). After the due date and time, the system locks the assignment and a student can only continue working by requesting an extension. Students can accept an automatic extension with a 20% penalty on points earned after the due date or they can wait for their instructor to grant a manual extension. The In-Class assignments contain 6-10 questions based on the current lecture and are usually designed to be completed before the end of class. Homework assignments contain 8-15 questions based on the previous lecture and are designed to be completed by the first 15 to 20 minutes of the next class meeting.

OPREP quizzes, practice examinations and simulated examination assignments usually remove access to all learning tools. An OPREP Quiz consists of 4-10 questions and covers topics from the previous lecture. Once again, each student has the same type of questions with a similar level of difficulty; however, the order of the problems and algorithmically generated numbers in each problem are different. Most quizzes are designed to be completed within 10 to

30 minutes of class. The majority of the quizzes require students to submit the entire assignment (rather than one question at a time) before WebAssign provides any feedback. After the due date and time, the system locks the assignment and students cannot request extensions. Some OPREP quizzes are given at the beginning of class and can provide students more incentive to be punctual.

OPREP practice examinations (i.e., Practice Midterm, Practice Final Exam) usually consist of 20-27 questions covering all relevant topics. Students must submit the entire assignment (rather than one question at a time) before WebAssign provides any feedback. After submitting the entire assignment, the students can see their grades and compare their answers to the correct answers. If a student is unsatisfied with his/her score, then the practice examination can be redone through a ‘new randomization’; however, all of the questions will change. Each student has the same type of questions with a similar level of difficulty; however, the order of the problems and the algorithmically generated numbers in each problem are different. Every attempt of the assignment has the same type of question with different values every time. In addition to being algorithmically generated, many questions draw from separate pools of items.

There are at least two versions of each practice examination. The Practice Midterm without help has no learning tools and the entire assignment must be submitted. The Practice Midterm with help has learning tools and may allow submission by question or by assignment. For the practice examinations with help that allow submission by question, students can request a new randomization at the question level instead of the assignment level. From time to time, the practice examination is used as a simulated examination. Access to the learning tools is eliminated and no notes or additional help is allowed. Students take the practice examination in a proctored testing environment and may review their performance immediately after submitting the entire assignment. Simulated examinations are intended to give students a realistic picture of their current knowledge and what they need to work on.

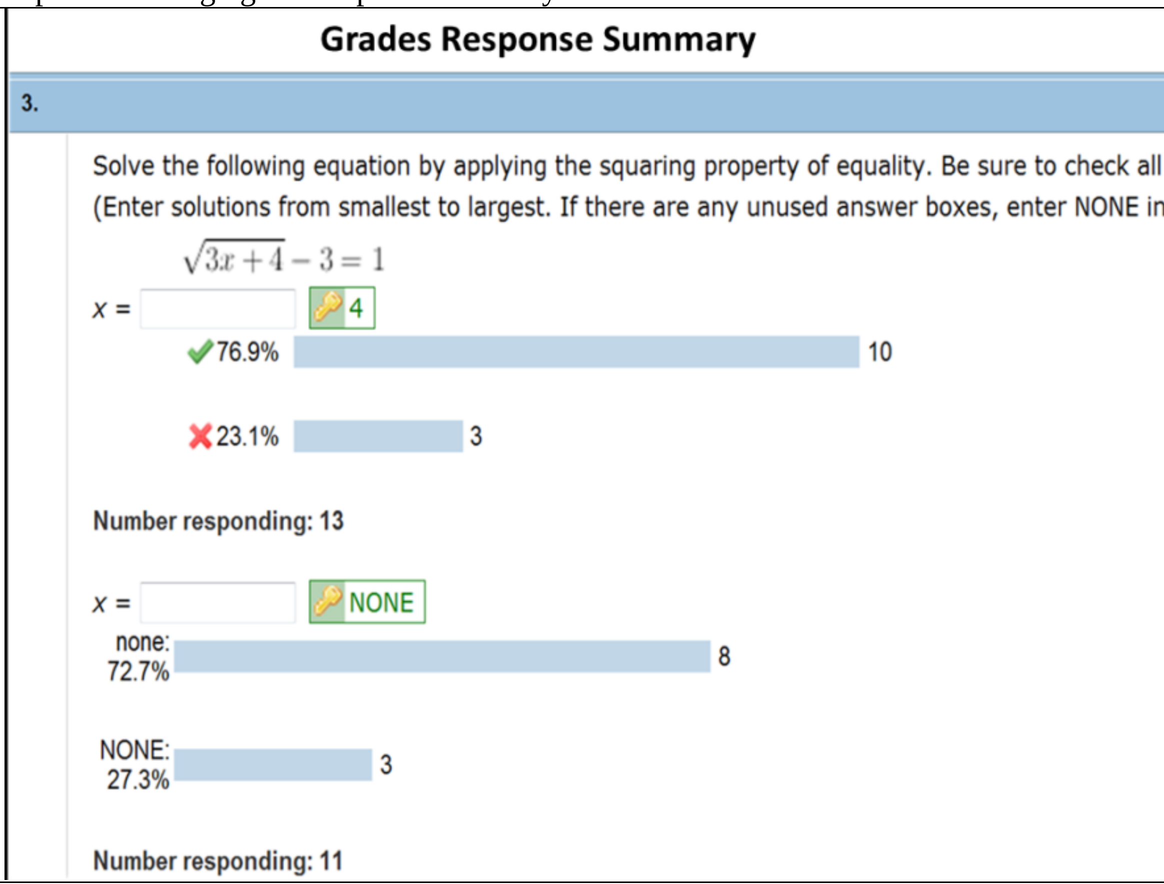
OPREP/WebAssign Implementation

On the first day of class, the instructor requires that all students sign up for WebAssign, explore the system and start an assignment. This sets a standard about the role and importance of WebAssign for a student's success in the course. Each student has access to the Internet because either the class meets in a computer laboratory or the student is using school-owned laptops/ netbooks. Some students may use other devices such as a tablet or personal laptop. On a typical day the first 15-30 minutes is designated for homework review. For example, if class starts at 10 am then the homework assignment is generally due between 10:15 and 10:30 am. After this time the system locks the assignment and a student can only continue working by requesting an extension. Students walk into class and immediately sign onto WebAssign. They work with their peers to complete their homework assignments and ask the instructor questions. The instructor encourages the students to work together in learning communities and the teacher is not concerned about cheating on homework on in-class assignments because of the design of the assignments. The student to share ideas and possible solutions. All students have the same types of problems with a similar level of difficulty; however, the numbers in each problem are algorithmically generated and the order of the problems differs.

The transparency of WebAssign allows the instructor to quickly analyze his students' performance on multiple levels. For each assignment the instructor can see the number of students responding to each questions and the percentage answering correctly via the grade response summary as depicted Figure 3.3. This transparency allows an instructor to see exactly what problem the class is struggling with by focusing on the questions with the lowest number of responses and/or highest percentage of incorrect answers. In the example illustrated in Figure 3.3, if a class contained 26 students who normally respond and only 13 submitted an answer then that may mean that half the class did not attempt the question or struggled with the problem.

Figure 3.3

Sample WebAssign grade response summary

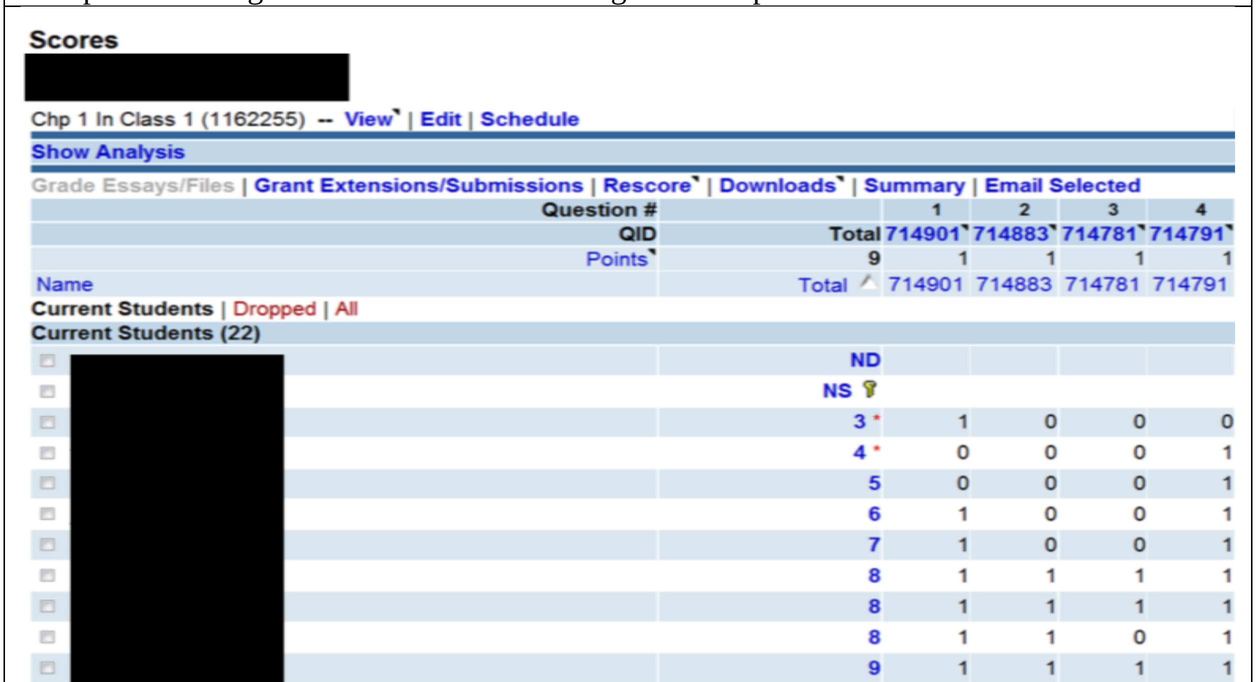


In addition to the transparency that the system offers on each assignment, WebAssign also provides transparency on the individual level (for each student) and category level (for each set of assignments) as depicted in Figures 3.4 through 3.6. Figure 3.4 displays a snapshot of WebAssign score screen, which allows the instructor to sort students based on the score on a specific assignment or sort them by their performance on a particular question within that assignment. This quickly allows the instructor to identify those students in need of intervention.

From the score screen, an instructor access individual student responses on a specific assignment including all answers the student submitted per question juxtaposed with the correct answers.

Figure 3.4

Sample WebAssign scores view / student assignment responses



Scores

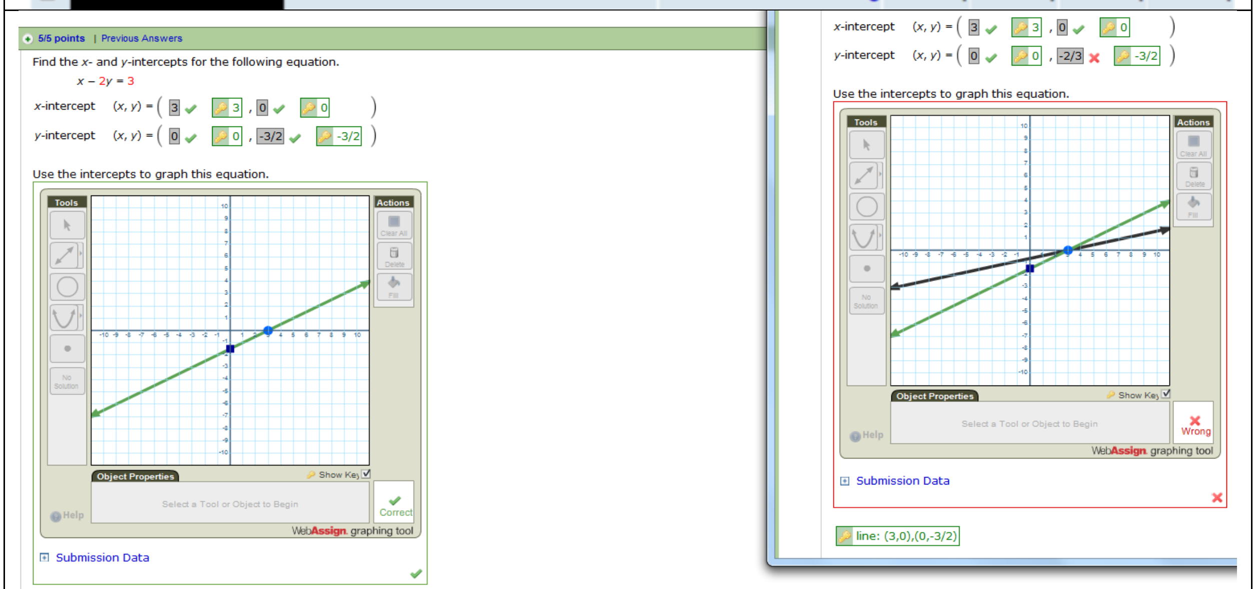
[redacted]

Chp 1 In Class 1 (1162255) -- View | Edit | Schedule

Show Analysis

Grade Essays/Files | Grant Extensions/Submissions | Rescore | Downloads | Summary | Email Selected

		1	2	3	4
Question #		1	2	3	4
QID	Total	714901	714883	714781	714791
Points	9	1	1	1	1
Name	Total	714901	714883	714781	714791
Current Students | Dropped | All					
Current Students (22)					
[redacted]	ND				
	NS				
	3	1	0	0	0
	4	0	0	0	1
	5	0	0	0	1
	6	1	0	0	1
	7	1	0	0	1
	8	1	1	1	1
	8	1	1	1	1
	8	1	1	0	1
	9	1	1	1	1



On the individual level an instructor can also view the students work if he made it mandatory for the student to submit their work. This Show My Work feature, as depicted in Figure 3.5, addresses the concern instructors expressed in the AMS homework software (2009) survey about students not showing their work.

Figure 3.5

Sample OPREP/ WebAssign show my work feature

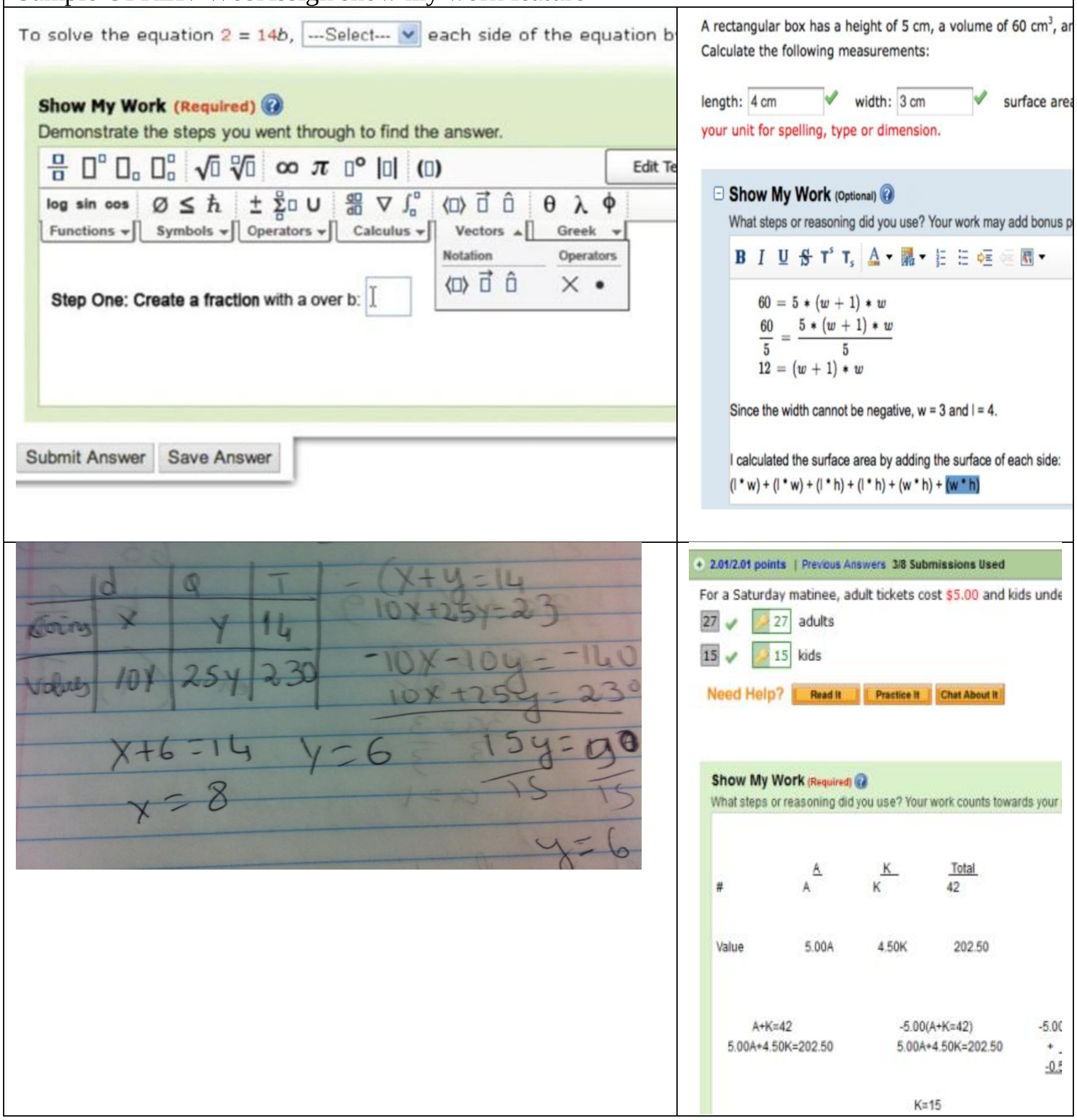


Figure 3.6 displays a snapshot of WebAssign gradebook, which tracks students' overall performance and provides instructor with descriptive statistics of each category of assignments. The gradebook allows the instructor to sort students based on their overall average or assignment category average. An instructor can view descriptive statistics for any subsets of students selected and recognize patterns in their performance. For example, isolating the subset of students who are currently failing can allow instructor to identify the most critical assignment category and develop a plan for intervention. From the gradebook screen, an instructor can select a student and access a summary of that student's assignment history including a log of time spent and activities on each assignment.

Figure 3.6

Sample WebAssign gradebook

GradeBook

[redacted]

Page Tools

Go to GradeBook for...

Update | Settings | Wizard

Averages Last Updated: Dec 30, 2009 06:26 PM EST

Assignment Category [# in Category / M = Manual]	Grade	Final	Homework [8]	Test [1]	In Class [6]	Compass [M]	Final Exam [M]	Midterm [M]
Weight Toward Final Grade [# dropped]		100	15 [2]	5	25	15	25	15
Class Average (mean) less...		83.30	85.33	74.32	84.04	90.48	82.07	77.91
median		87.75	92	86.96	94.44	100	81	77.80
standard deviation		11.76	17.85	28.93	18.91	29.35	7.39	14.46
min/max		47.90/96.58	43.64/100	7.69/100	41.30/100	0/100	70.50/95.40	47/98
Name	Grade	Final	Homework	Test	In Class	Compass	Final Exam	Midterm
Dropped | Current Students | All								
Current Students (21)								
[redacted]	A	96.58	100	100	100	100	89	95.50
	A	93.78	100	100	100	100	80.80	90.50
	A	93.62	86.60	100	97.22	100	86.50	98
	A	93.25	97.56	93.48	90.94	100	95.40	82.40
	A	92.65	97.75	95.65	83.33	100	93.50	93.30
	A	92.02	91.89	100	100	100	86.50	77.40
	A-	91.57	94.59	65.22	90.35	100	91	91.90
	A-	91.23	100	66.74	100	100	80.40	85.30
	A-	90.41	97.98	100	95.24	100	82	76
	B+	88.23	91.36	7.69	95.45	100	86.50	91
	B+	87.75	89.19	56.52	96.89	100	85.50	73
	B	86.94	100	91.30	96.97	100	79	55.90
	B	85.28	92	86.96	99.24	100	77.50	53

The instructor uses the real-time analytics of an OPREP (Figures 3.1, 3.2 and 3.4) to improve student achievement in developmental mathematics by tailoring pedagogy (e.g., lecture, class discussion, group work, one to one tutoring) to the needs of each class and each student based on real-time performance on in-class assignments.

Effectively employing the grade response summary and the other tools described in Figures 3.3 through 3.6 can allow the instructor to transform the classroom. After the homework review, the instructor starts lecturing. To focus student's attention on the board, the lecturer utilizes computer laboratory management software (e.g., Vision or Insight) to shut off the monitor. Throughout the lecture topics are introduced and discussed by the class in a traditional fashion. Instead of reviewing multiple examples on the board the instructor chooses a few problems with the appropriate level of scaffolding for the students to attempt and discuss as a class. During the lecture after discussing an example, the students are directed to find a similar example on the in-class assignment on WebAssign. As we have seen, the in-class assignment is designed to be integrated into the lecture. The instructor can use tools in the score screen to determine the real-time progress of each individual student and the grade response summary for progress and pace of the entire class. This allows the instructor to intervene at individual level (with one to one tutoring) or on a class level by blocking screen and discussing difficult question on the board.

The students can be constantly engaged and gain a sense of satisfaction when correctly answering questions and completing assignments. In order for a student to move to the next assignment before the designated time, that student may need to complete a prerequisite with a score of at least 75%. An advance student moves at his or her own pace by accessing future assignments early because that student adequately completed the prerequisite assignments well before their peers and sometimes before the relevant lecture through the use of learning tools and other resources. The advantage of allowing students to start future assignments is that it can help the instructor keep students engaged. The advance students read the textbook before the next lecture and use the learning tools to solve problems that the class has yet to cover, potentially increasing the quality of their class participation. In this environment, where group work is encouraged, the advance students naturally become tutors to their peers and function as bellwether students.

The instructor provides feedback to students when requested. WebAssign's learning tools link the students to the relevant section of their textbook, grants access to pertinent video lectures and provides step-by-step tutorials for student utilization. This, along with a group work environment, affords the instructor more time to provide more attention where needed and one-to-one tutoring to those who are struggling. The instructor need not wait until struggling students ask questions; he identifies those that are moving at a significantly slower pace than their classmates and initiates the attempt-feedback-reattempt conversation. "How many times has the fear of being embarrassed prevented a student from asking the teacher to explain a concept for the second, let alone the third or fourth time? These issues are real. They impact learning" (Shelton, 2013, p. 4). Through this one-to-one tutoring the struggling students move closer to the classes pace and eventually initiate the attempt-feedback-reattempt conversation like their peers. The transparency of the OPREP allows the instructor to reach previously unreachable students.

CHAPTER IV
RESULTS

This chapter addresses the four research questions for this study. The context of the questions is briefly summarized, the questions are restated, followed by the results and interpretations completed from the analysis.

Research Question 1: Online Preparation and Rigorous Enhancement Platform Features

1. What OPREP features did students find most useful? Why? How often did they use these features?

The questionnaire asked 129 former students questions about the frequency and usefulness of specific features (Grades, Personal Study Plan, Assignment Extensions, Announcements, Calendar, Resources, Notifications) available on WebAssign. WebAssign features are defined as functionalities that exist within the OPREP but exist outside OPREP assignments. Table 4.1 shows the frequency with which students used the features of WebAssign. A frequency score of 1, 2 and 3 represents, respectively, “not at all”, “occasionally” and “frequently”. The WebAssign features most frequently used by students were viewing grades on WebAssign and receiving email notifications about assignments. Of the 129 students, approximately 81% used email notifications and other communication tools frequently and approximately 84% viewed their grades frequently.

On the other end of the spectrum, only 42% reported using the personal study plan feature and approximately 47% used assignment extensions. The students were instructed to set up email notification preferences but they were not required to use any other feature. The students were introduced to these functionalities at the beginning of the course and used them at their discretion. Student use of and performance on the personal study plan was not factored into their grades.

Table 4.1

Student usage of WebAssign highlighted features

OPREP Feature	Not at All (1)		Occasionally (2)		Frequently (3)		Total	Mean	Standard Deviation
View your Grades on WA	1.55%	2	13.95%	18	84.50%	109	129	2.83	0.42
Used the Personal Study Plan	20.93%	27	37.21%	48	41.86%	54	129	2.21	0.77
Request Assignment Extensions in WA	10.08%	13	43.41%	56	46.51%	60	129	2.78	0.49
Read Announcements on WA /Used links in Announcements	3.10%	4	26.36%	34	70.54%	91	129	2.67	0.53
Viewed the Calendar for Assignment due dates and times in WA	8.53%	11	18.60%	24	72.87%	94	129	2.64	0.63
Used Resources that your instructors posted in the Resource section	2.33%	3	24.03%	31	73.64%	95	129	2.36	0.66
Received email Notifications about Assignments & other Communications	3.10%	4	16.28%	21	80.62%	104	129	2.21	0.77

Examining the student comment sheets and students' open-ended answers about the rationale behind their usage of these features (Grades, Personal Study Plan, Assignment Extensions, Announcements, Calendar, Resources, Notifications) allowed the researcher to critically analyze the emergent themes. Figure 4.1 depicts a word cloud generated by the text students used to explain if the OPREP features were useful. The words that appear with higher frequency in the students' open-ended responses are more prominent in the word cloud. The majority of the respondents appear to believe that the features were useful; the prominent words were grades, track, time and extensions. Analyzing the student's perceptions of the features usefulness and the students' evaluation comments to under the context revealed the emergent themes. According to the respondents, the most important feature was the students' ability to immediately view their overall grades at any instance during the semester.

Figure 4.1

Word Cloud: Text students used to explain if the WebAssign features were useful

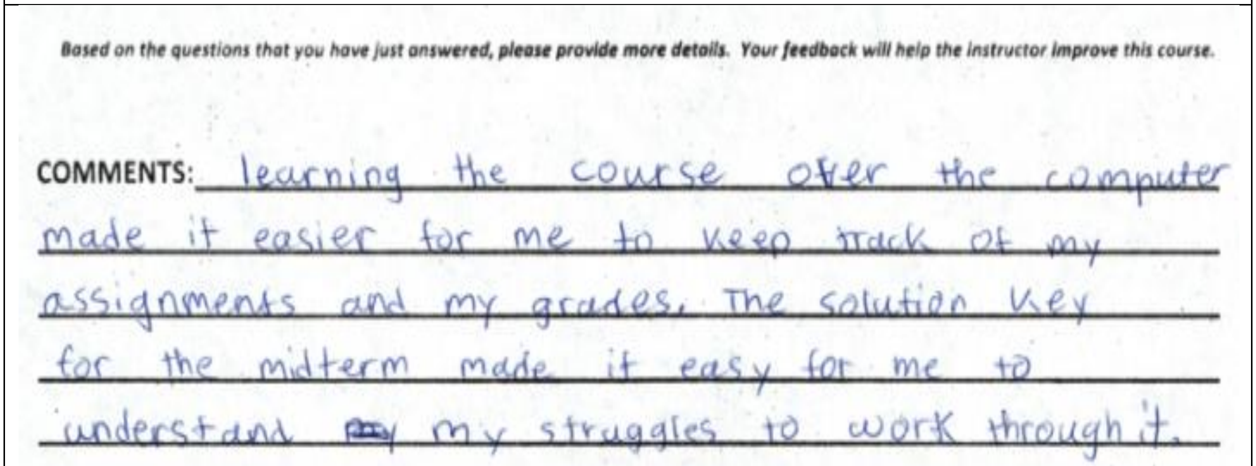
Student viewing their grades functioned as a constant progress report. One student stated,

> The ones that I found useful to me were the grades system and the extension system. Being able to check your grades at any time is extremely helpful and can sometimes be a good wake-up call (Student 1, Questionnaire, January 23, 2016).

The theme of students tracking their grades also emerged in the student comment sheets, as shown in Figure 4.2.

Figure 4.2

Student evaluation artifact: comment sheet


Based on the questions that you have just answered, please provide more details. Your feedback will help the instructor improve this course.

COMMENTS: learning the course over the computer made it easier for me to keep track of my assignments and my grades. The solution key for the midterm made it easy for me to understand my struggles to work through it.

The following student quotation is representative of most of the questionnaire respondents.

> Great features. Grades - keeps me motivated and aware of my current progress. Excellent. Extensions - relieves stress Announcements - great way to get live info from prof [professor]. The others I used only occasionally. (Student 2, Questionnaire, January 23, 2016)

Though time extensions on assignments were not used frequently (only 47%), students' found the extensions were essential because they offered the students a chance to improve their grades when necessary. Extensions functioned as an outlet for students to reduce their stress concerning their grade on a particular assignment and its effects on their overall grades in the course. Tracking their progress in terms of their overall grade at any time was the essential optional feature (excluding the notification that students were instructed to set up). Even students who preferred the traditional paper-based homework assignments saw the value of WebAssign's immediate feedback on assignments and the ability to track grades. One student stated,

> Very convenient and reliable. Instant feedback and grades were extremely useful. I would rather complete math problems with a paper and pen but the features that came with WebAssign such as feedback and checking your current grades far outweigh that. (Student 3, Questionnaire, January 23, 2016)

Tracking grades and using the learning tools to increase their knowledge impacted adult student's motivation to learn. Comments from two students who were interviewed expressed their initial concerns due to mathematics anxiety. Colyar said, "I was mad at the college for making me take the course to graduate. I was just so nervous and felt I'd never be able to get math so I decided not to show up the first day of class" (Strang, 2015, p. 1). Kong stated, "Math has always been my weakest subject. I definitely have math anxiety because I never really learned it when I was younger, so now math is my most feared subject" (Strang, 2015, p. 1). Their initial low mathematics self-efficacy changed over the semester through constant progress reports and learning tools available through WebAssign.

> 'If you get a problem wrong the system shows you exactly why you got it wrong,' Colyar said. 'I'm like okay, now I know how to fix it and can be sure I really understand before I move on to the next problem…It was really easy and straightforward,' Kong said. 'If I got stuck I would just watch one of the videos…It was something new every time so it wasn't tedious or repetitive. Once I saw I was making progress it encouraged me to keep going and to keep learning' (Strang, 2015, p. 1-2).

Seeing that their effort lead to a correct answer, a completed assignment or increase in overall grade resulted in a sense of accomplishment, impacted their self-esteem and encouraged productive persistence to successfully complete the course. Fidishun (2000) stated, "Activities that build students' self-esteem, or sense of accomplishment through, for example, the completion of goals or modules that can be checked off in a sequence, may help motivate completion of a longer lesson” (p. 4).

Research Question 2: OPREP Learning Tools

2. What OPREP learning tools did students find most useful? Why? How often did they use these learning tools?

The questionnaire asked students about the frequency and usefulness of specific OPREP learning tools (Read It, Watch It, Practice It, Master It, Practice Another Version) available on WebAssign. Learning tools are defined as functionalities existing within OPREP assignments; they differ from OPREP features because OPREP features exist outside OPREP assignments. Table 4.2 illustrates the frequency with which students use each highlighted OPREP learning tools. A frequency score of 1, 2 and 3 represents “not at all”, “occasionally” and “frequently”, respectively.

The WebAssign learning tools used most frequently by the students were watching video lectures, using Practice Another Version and Practice It (step by step interactive tutorials). Of the 129 students, approximately 64% frequently used the Watch It, 66% used Practice Another Version frequently and approximately 67% used Practice It frequently. While explaining the usefulness of the immediate feedback of the learning tools, one student referred to working outside the classroom. “If you were by yourself trying to answer the problems there were different ways to learn how to look at the problems. I used Practice It a lot” (Student 4, Questionnaire, January 23, 2016).

Table 4.2

Student usage of WebAssign learning tools

OPREP Feature	Not at All (1)		Occasionally (2)		Frequently (3)		Total	Mean	Standard Deviation
"Read It"/ eBook/ YouBook	7.75%	10	51.16%	66	41.09%	53	129	2.33	0.62
"Watch It" / Video Lectures	6.20%	8	29.46%	38	64.34%	83	129	2.58	0.61
"Practice It"/ Step by Step Interactive Tutorials	4.65%	6	27.91%	36	67.44%	87	129	2.63	0.57
"Master It"/ Additional Concept Mastery Tutorials	6.20%	8	34.11%	44	59.69%	77	129	2.53	0.61
"Practice Another Version"	4.65%	6	29.46%	38	65.89%	85	129	2.61	0.58

On the other end of the spectrum, only 41% reported using the Read It button to read the electronic version of the textbook. It is important to recognize that students do not automatically turn to the textbook for help to answer questions; however, it must be noted that Read It was the least used learning tool. The students were not required to use any learning tool. They were introduced to the learning tools at the beginning of the course and students used them at their discretion. The students naturally developed tendencies for their preferred learning tools based on their learning styles. Students recommended specific tools to their peers.

When asked if WebAssign worked well with their learning style, 86% of students responded affirmatively, 4% responded negatively and the remaining 10% provided responses that were neutral or not applicable to the question. Of the seventy-four students who responded to this question, three said that it did not work well with their learning style and unfortunately only one elaborated. One student shared: "No. I am not good with online work" (Student 5, Questionnaire, January 23, 2016). Another student stated, "I like WebAssign but I think being present in a class is better for me" (Student 6, Questionnaire, January 23, 2016). One student with a neutral response straddled the fence. “Yes and no. Yes, if I have a motivation to pass and no if I get lazy and quit” (Student 7, Questionnaire, January 23, 2016). Motivation in this context is intrinsic because the ramifications of failing (time, finances and opportunities) and having to repeat this prerequisite course can be considered external motivators for all students. Additional extrinsic motivation can come from the instructor. One student stated, “I learned more because the software was very easy to use and most importantly my teacher was very spectacular and motivating” (Student 8, Questionnaire, January 23, 2016). Another student shared,

> WebAssign works well with my learning style because there are multiple resources the website offers for me to learn from ("read it", "practice it", "watch it” etc.) and the website showing the work on how to solve a problem step by step, helped me visualize my mistakes and learn from them. (Student 9, Questionnaire, January 23, 2016)

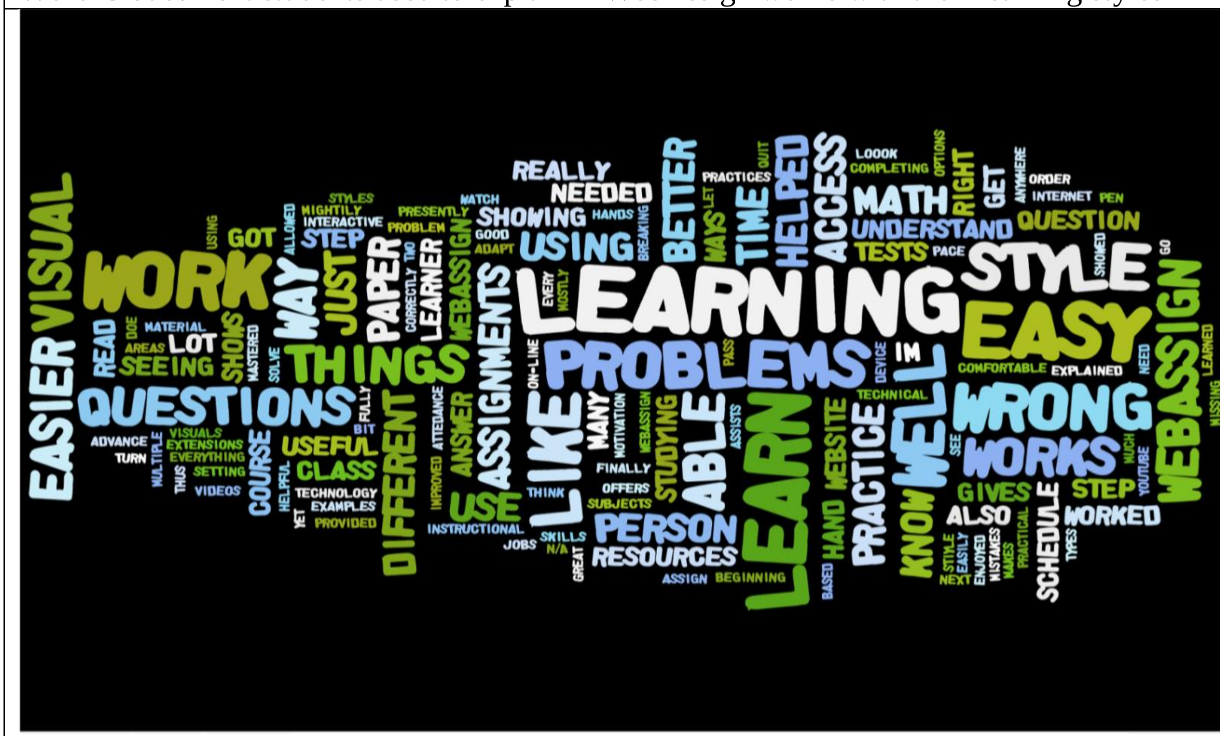
Multiple learning tools are referred to explicitly and implicitly by one student: “It works well for my learning style because it gives a lot of options for studying like videos, tutorials, and practice tests” (Student 10, Questionnaire, January 23, 2016).

Approximately 12% of students self-identified as visual learners or mentioned a lecture video contributing to their learning. One student said, “Yes absolutely. I’m a visual student, I like seeing my grades and attendance” (Student 11, Questionnaire, January 23, 2016). This respondent mentioned grades deriving from the gradebook, which is defined as an OPREP feature because it exists outside OPREP assignments, rather than as an OPREP learning tool, defined as a functionality that exist within OPREP assignments. When asked about WebAssign working with their learning style, approximately 12% mentioned the importance of feedback. “Honestly, it really does. Say if you got an answer wrong it shows you steps on how you got that question wrong so you know next time not to get it wrong and you learn from it" (Student 12, Questionnaire, January 23, 2016).

Figure 4.3 depicts a word cloud generated by the text from the students' open-ended answers used to explain the synergy or lack of synergy that using WebAssign had with the students' learning styles.

Figure 4.3

Word Cloud: Text students used to explain if WebAssign works with their learning styles



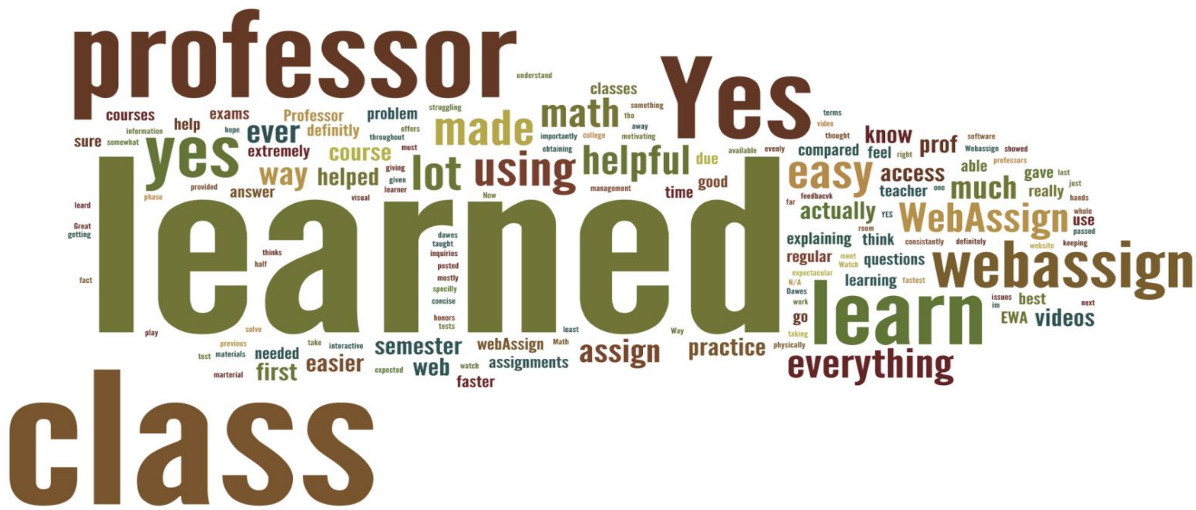
The macro level feedback (e.g., cumulative grade) and micro level feedback about student performance on each question within an assignment and strategies to find solutions to those problems were important to the respondents. "WebAssign was the way for me to know my weak areas in math and thus I learned to build my math skills" (Student 13, Questionnaire, January 23, 2016). Approximately 15% of the students referred to being able to practice through the step-by-step tutorials available through the Practice It or Master It learning tools that exist within the assignments. "It does [work with my learning style] because there is plenty of resources and practice to go over in order to fully understand and master it" (Student 14, Questionnaire, January 23, 2016).

When asked whether they learned more or learned less in this class compared to other mathematics' classes where they did not use WebAssign, 81% of students responded with more (or affirmatively), 5% responded with less (or negatively) and the remaining 14% provided responses that were neutral or not applicable to the question. Of the eighty-two students who responded to this question, only four said that they learned less. Unfortunately, only one student elaborated. One stated: "Less because I wasn't physically writing everything out, it was all on a computer" (Student 15, Questionnaire, January 23, 2016). A different student, with a response that was considered not applicable to this specific question, echoed the recurring theme of feedback. "WebAssign is helpful in terms of keeping all homework in a concise place and being able to receive feedback right away" (Student 16, Questionnaire, January 23, 2016).

Crediting the instructor was a recurring theme as students explained why they learned more or less. One student stated, "I did learn a lot but I think I would have learned more with a teacher present available to answer any inquiries I have" (Student 17, Questionnaire, January 23, 2016). Another said, "Not really, it was mostly because of my prof. consistently giving me assignments" (Student 18, Questionnaire, January 23, 2016). The importance of the teacher's/ professor's role was prevalent among the responses. Figure 4.4 depicts the most prevalent words in the students' text responses.

Figure 4.4

Word Cloud: Text students used to explain comparisons on learning Mathematics with or without WebAssign



Approximately 25% of the students who compared how much they learned mentioned the importance of their teacher.

> I've learned by far the most in this class with the help of my Professor & WebAssign. Before this math course I was a failing student obtaining extremely low scores on my examinations such as 7% out of 100 and 36%. Now [in] this course, I am getting at the least an 80 or above on all my examinations. I can definitely say YES I learned more using WebAssign. (Student 19, Questionnaire, January 23, 2016)

Some student explanations credited solely the instructor. “Yes I did. The professor I had was very caring and helped me learn way more than I thought I ever could” (Student 20, Questionnaire, January 23, 2016). The following response is from a student who repeated Elementary Algebra at least twice. “Yes, Professor is AMAZING! I learned more in his class the first half of the semester than I did throughout the whole last semester class” (Student 21, Questionnaire, January 23, 2016). Other students who stated they learned more credited the combination of their instructor and WebAssign.

> I think [I] learn more in class and on WebAssign because in WebAssign it gave me questions to practice on and in mathematics class my prof. would go over a problem that we were struggling with. (Student 22, Questionnaire, January 23, 2016)

In addition, one student stated learning more with WebAssign. “More because the interaction with the professor and the videos in WebAssign helped me more than a regular professor would in a regular class” (Student 23, Questionnaire, January 23, 2016). During an interview, a student shared,

> The combination of a very supportive professor and Enhanced WebAssign definitely helped me. If EWA enabled me to pass math even when I thought I was doomed, I believe anyone can succeed with it. (Strang, 2015, p.1)

The desired increase in student achievement in developmental mathematics through use of an online preparation and rigorous enhancement platform may depend on mathematics instructors’ implementation strategies and the students’ experiences using an OPREP. One student stated that WebAssign was “easy to use with correct instruction. I have used this program across two educators- proper instructions is definitely necessary” (Student 24, Questionnaire, January 23, 2016). The comment came from a student who had repeated this developmental course with different instructors. She emphasized proper instruction because the instructors had different WebAssign implementation strategies. Another multiple repeater stated,

> None of my previous professors used it the way [he] did. He used it in such a way that if you got a problem wrong, the solution would tell you if you got it wrong so you could go back and check the answers and see how you got it wrong. (Strang, 2016, p.3)

When using WebAssign, an instructor's implementation strategy is essential to student achievement.

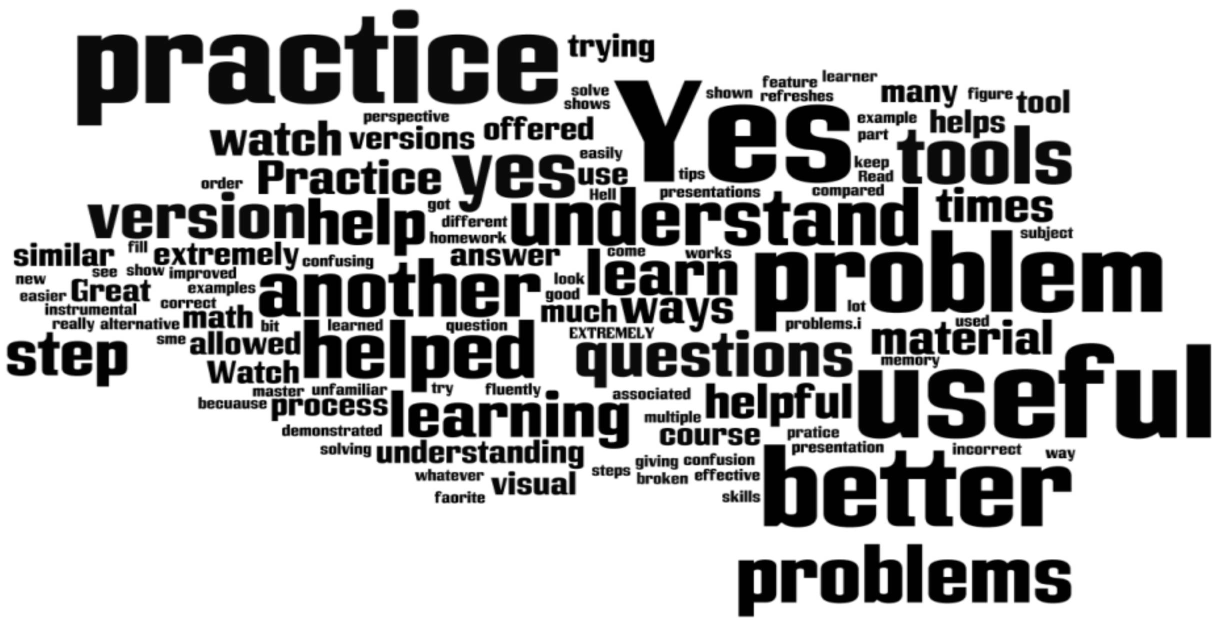
Students wrote about the organization of WebAssign being essential to their learning process. "I learned more because of WebAssign because of how clear and organized it was," said one student (Student 25, Questionnaire, January 23, 2016). A student exclaimed, "I definitely learned more, I had issues learning with time management before but the materials on the website definitely helped me and made things much easier and effective" (Student 26, Questionnaire, January 23, 2016).

Several students also credited the OPREP learning tools with helping them learn more compared to their previous mathematics classes. Some implicitly referred to the feedback in terms of strategies to find solutions provided by using multiple learning tools. "I learned more because there were different explanations given to me and it made the learning process go faster" (Student 27, Questionnaire, January 23, 2016). Other students explicitly stated the learning tools they relied on, such as "Read It" and "Watch It", etc. made it very easy to get through the course" (Student 28, Questionnaire, January 23, 2016). Another student stated, [I learned] "way more, I'm an interactive learner so WebAssign provided exactly what I needed" (Student 29, Questionnaire, January 23, 2016). Student referred to these learning tools and their own learning styles without prompting. "I learned more [in] this class due to the "watch it" videos, as I said before I am a visual kind of person and if I did not understand something I would play the video over and over" (Student 30, Questionnaire, January 23, 2016).

Examining the students' open-ended answers about the rationale behind their learning tool usage allowed the researcher to identify emergent themes. Figure 4.5 depicts a word cloud generated by the text students used to explain if the learning tool were useful. The words that appear with higher frequency in the responses are more prominent in the word cloud. Evidently that the majority of the respondents believe the learning tools were useful for “practice”, described what they thought of the learning tools, as “useful”, “better”, and “help[ful]”. Revisiting the data for the context allowed classification of these categories and the discovery of the central phenomenon.

Figure 4.5

Word Cloud: Text students used to explain if WebAssign learning tools were useful

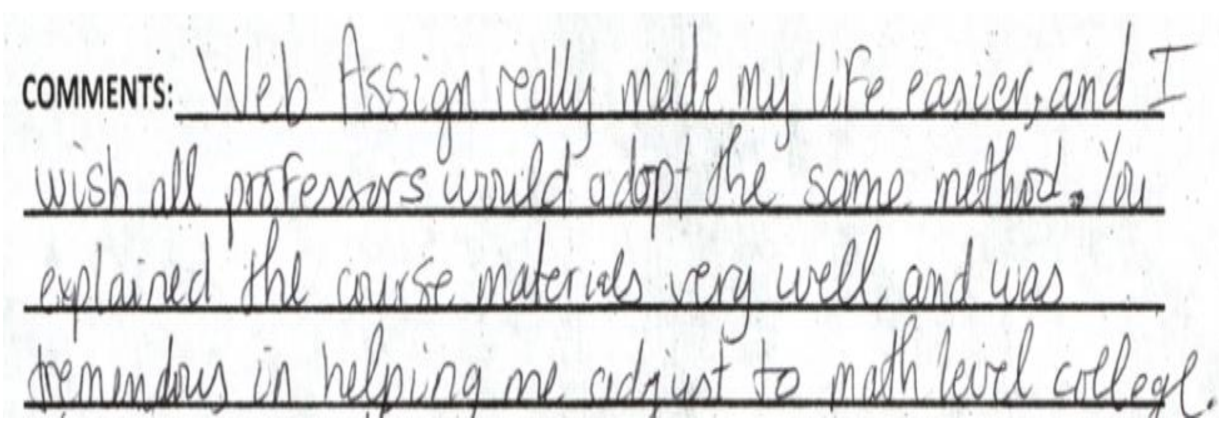


The central phenomenon was the student’s ability to access immediate relevant feedback available for each question on each assignment. The feedback went beyond knowing whether answers were wrong or right. The students used the learning tools to understand the context of a problem, learn the approach to solve a problem or identify their own mistakes when attempting to solve the problem. While commenting on the learning tools, one student stated, “At times you have only part of a problem incorrect and the alternative versions help you to see the process from the correct perspective” (Student 31, Questionnaire, January 23, 2016). A different student wrote, "If I cannot go to class or I forgot what professor taught, I would use those tools to learn or remind myself" (Student 32, Questionnaire, January 23, 2016). The learning tools on WebAssign addressed Bloom's two-sigma problem by providing one-on-one individualized instruction for each student when needed, especially outside the classroom.

On a micro level, students use WebAssign's learning tools to receive one-on-one individualized instruction. One student captured these sentiments, "WebAssign is like having the presence of your professor wherever / whenever logged in" (Student 33, Questionnaire, January 23, 2016). Several students express desire to use WebAssign in future classes. "I hope my next class offers WebAssign, I feel so comfortable using it" (Student 34, Questionnaire, January 23, 2016). In general, the students find this immediate feedback not just useful but essential to their learning process. The immediate feedback provided through WebAssign in concert with feedback from the professor was highly valued by the students, as depicted in Figure 4.6 a comment from one student.

Figure 4.6

Student evaluation artifact: a hand written comment sheet


COMMENTS: Web Assign really made my life easier, and I wish all professors would adopt the same method. You explained the course materials very well and was tremendous in helping me adjust to math level college.

Research Question 3: Grade Differences in OPREP Assignments

3. Is there a statistically significant difference in the students' grades on OPREP assignments between students who pass the course and students who fail the course?

In order to pass this Elementary Algebra course, students must pass, as an exit examination, a comprehensive Computer-Based Test (CBT) final examination administered and scored by the college's testing department. The comprehensive CBT exit examination represents 35% of the student's final grade. The examination consists of 25 equally weighted, multiple-choice questions, with distractors, worth four points each. Students without special accommodations have 100 minutes to attempt to achieve a 60% (15/25) passing grade. A University-wide committee of staff and faculty members, including Mathematics subject matter experts, created the CBT exit examination.

In addition to the CBT exit examination, the Mathematics Department also requires each instructor of an Elementary Algebra section to administer a paper-delivered departmental final examination before the CBT exit examination. This paper- delivered test (PDT) consists of 10 multiple-choice questions and 12 short-answer questions. The comprehensive departmental final examination was created by the department's Developmental Mathematics committee and, is graded by the section instructor and counts for 5% of the student's final grade. Prior to the adoption of the CBT final examination, the PDT departmental final was used as the exit examination. It remains as a relic that can be used as a wake-up call before the CBT final examination. Only the CBT final examination functions as an exit examination; its delivery, grading, administration and weight in terms of the cumulative average differs from the PDT, known as the departmental final examination.

Performance on final examination. Table 4.3 contains descriptive statistics for all the categories of assignments associated with this Elementary Algebra course, including the two CBT examinations (exit and Compass Algebra entrance) and PDT (departmental final and midterm) that exist outside the OPREP assignments. The departmental midterm examination is worth 15% of the student's final grade, the departmental final examination is 5% and the CBT exit examination is 35%.

Table 4.3

Descriptive statistics of continuous variables: number of observations, arithmetic mean, standard deviation, sum, minimum and maximum

	Simple Descriptive Statistics						
	Variable	**N**	**Mean**	**Std Dev**	**Sum**	**Minimum**	**Maximum**
OPREP Assignments	**Quiz**	261	66.27	30.08	17297	0	111
	In Class Assignments Average	261	73.85	26.18	19274	0	100
	Homework Average	261	72.82	24.38	19007	3.67647	101
	Midterm Practice	249	54.69	35.56	13617	0	100
	Cumulative Quiz	163	60.54	32.50	9868	0	100
	Practice Final Exam	125	44.39	32.64	5549	0	100
	Practice CBT Final	187	59.66	31.48	11156	0	100
OPREP Metrics for Time & Activity	**Aggregated time spent**	261	2514.00	1339.00	656272	175	8712
	Aggregated activities	260	491.63	210.26	127824	44	1334
	Aggregated log-in days	261	31.79	11.06	8297	1	68
	Number of log-ins	154	37.11	15.42	5715	1	84
	Attendance	261	79.70	16.27	20802	25	104
Exams (non-OPREP)	**CBT Final Exam (Exit Exam)**	261	73.66	18.58	19224	20	100
	Departmental Final Exam	249	69.05	24.41	17194	0	100
	Departmental Midterm Exam	249	73.57	22.42	18318	0	100
	Algebra Compass Entrance Exam	238	21.92	6.28	5217	15	38
	Pre-Algebra Compass Placement	240	38.05	18.79	9131	17	97

Analyses of students who passed and who failed the course. A student who passes the CBT Final examination passes the Elementary Algebra course. Tables 4.4 to 4.7 compare students who pass the course to students who fail. There is a column headed CBT Exit Examination Status. Tables 4.4 to 4.7 have two rows corresponding to students who passed as described above and those who failed by scoring below 60. In order to determine statistically significant differences between the performances of the two groups of students on their OPREP assignments, the investigator used a two-tailed t-test and the data was normally distributed. (The t-test is appropriate to use for continuous numerical data from an interval scale instrument such as the results of an examination. It can determine if the means of continuous numerical variables are statistically significantly different from each other beyond chance at a specified level of confidence.) The null hypothesis is that performance on the OPREP assignments of failing students and passing students does not differ by more than what is expected by chance.

Table 4.4

Two-tailed t-test comparing the OPREP quiz average (n = 261)

Variable: Quiz

CBT Exit Exam Status	N	Mean	Std Dev	Std Err	Minimum	Maximum
Pass	208	72.8320	25.9156	1.7969	0	111.1
Fail	53	40.5331	31.6934	4.3534	0	98.0556
Diff (1-2)		32.2989	27.1744	4.1813		

CBT Exit Exam Status	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
Pass		72.8320	69.2894	76.3746	25.9156	23.6415	28.6776
Fail		40.5331	31.7973	49.2689	31.6934	26.6019	39.2134
Diff (1-2)	Pooled	32.2989	24.0652	40.5325	27.1744	25.0221	29.7348
Diff (1-2)	Satterthwaite	32.2989	22.9073	41.6904			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	259	7.72	<.0001
Satterthwaite	Unequal	70.712	6.86	<.0001

Significant α= .05

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	52	207	1.50	0.0516

Not Significant α= .05

The two-tailed t-test in Table 4.4 compares average scores on the OPREP quiz assignments (quizzes administered through WebAssign throughout the semester) of students who passed versus students who failed. On average, students who passed the course had a higher OPREP quiz average by 32 % (73 % compared to 41 %). The two-tailed t-test in Table 4.4

shows that the means of the two groups are significantly different at the 5% confidence level (p-value < 0.0001 < 0.05). The probability of no significant difference between the OPREP quiz average of the students who passed and those who failed is less than 1 in 10,000 (< .0001). They are significantly different whether the groups have equal variances – pooled t-test— or unequal variances – Satterthwaite t-test.

The folded F statistic shows that the variances are not statistically significantly different (unequal) at the 5% level (p-value = 0.0516 > 0.05). The pooled t-test statistic and degrees of freedom were used to calculate the effect size, Cohen's d. The effect size for a 32-point difference in the average score is 0.96. This is considered large (above 0.8) based on Cohen's standard. An approximate effect size of 1.0 indicates that the OPREP quiz average score of the passing group, 73 %, is at the 84th percentile of the mean of the failing group, 41 %. The effect size correlation, $r_{Y1,}$ is 0.433. For a Cohen's d value of approximately 0.96, the amount of variance in the dependent variable, OPREP quiz average, that is accounted by membership in the independent variable, CBT exit examination status, groups (fail and pass) is 18.7 %, r_{Y1}^2.

All t-test comparisons for each variable were statistically significant different at the 5% level except for the Aggregated time spent. The p-value corresponding to the Aggregated time spent t-value of 0.92 is 0.3581, which is larger than the 0.05 alpha. Students who passed the exit examination spent on average 189.7 more minutes on WebAssign than students who failed. This is less than one sixth of a standard deviation in both groups as seen in Table 4.5. We fail to reject the null hypothesis that the means of the aggregate time spent on the OPREP of the group of students who passed the exit examination is the same as the mean of the group of students who failed.

Though the majority of the OPREP assignments and OPREP time and activity metrics had statistically significantly differences according to the t-test, only quizzes on WebAssign had a large effect size. All other OPREP assignments (In Class Assignments Average, Homework Average, Midterm Practice, Cumulative Quiz, Practice Final Examination, Practice CBT Final) had medium effect sizes (Table 4.8 includes a report of Cohen's d values). The statistically significant OPREP time and activity measures (Aggregated activities, Aggregated log-in days, Number of log-ins and Attendance) had small effect sizes.

Table 4.5

Two-tailed t-test comparing the OPREP Aggregated time spent average

Variable: Aggregated time spent

CBT Exit Exam Status	N	Mean	Std Dev	Std Err	Minimum	Maximum
Pass	208	2553.0	1284.7	89.0784	280.0	8712.0
Fail	53	2363.3	1536.1	211.0	175.0	7065.0
Diff (1-2)		189.7	1339.0	206.0		

CBT Exit Exam Status	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
Pass		2553.0	2377.4	2728.6	1284.7	1172.0	1421.6
Fail		2363.3	1939.9	2786.7	1536.1	1289.3	1900.6
Diff (1-2)	Pooled	189.7	-216.0	595.4	1339.0	1232.9	1465.1
Diff (1-2)	Satterthwaite	189.7	-266.9	646.3			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	259	0.92	0.3581
Satterthwaite	Unequal	71.616	0.83	0.4103

Not Significant

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	52	207	1.43	0.0843

Not Significant α= .05

The statistically significant OPREP time and activity measures (Aggregated activities, Aggregated log-in days, Number of log-ins and Attendance) had small effect sizes. All t-tests for the summative assessments (Midterm Examination, Departmental Final Examination, Algebra Compass entrance examination, Pre-Algebra Compass entrance examination) were statistically significant with large effect sizes. ACT's Algebra Compass and Pre-Algebra Compass examinations are computerized examinations designed like placement examinations to evaluate student skills. The Departmental Final and Midterm examinations are paper delivered tests (PDTs) graded by each Elementary Algebra section's instructor. The Midterm examination and the Algebra Compass entrance examination had the highest effect sizes, as seen in Table 4.8.

The t-test in Table 4.6 compares average scores on the PDT Midterm examination of students who passed versus students who failed.

Table 4.6

Two-tailed t-test comparing the non-OPREP midterm examination average

Variable: Midterm Exam

CBT Exit Exam Status	N	Mean	Std Dev	Std Err	Minimum	Maximum
Pass	198	78.1368	19.5487	1.3893	0	100.0
Fail	51	55.8163	24.1323	3.3792	0	94.5000
Diff (1-2)		22.3205	20.5592	3.2284		

CBT Exit Exam Status	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
Pass		78.1368	75.3971	80.8766	19.5487	17.7942	21.6900
Fail		55.8163	49.0290	62.6036	24.1323	20.1917	29.9984
Diff (1-2)	Pooled	22.3205	15.9618	28.6793	20.5592	18.8950	22.5473
Diff (1-2)	Satterthwaite	22.3205	15.0295	29.6116			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	247	6.91	<.0001
Satterthwaite	Unequal	67.839	6.11	<.0001

Significant α= .05

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	50	197	1.52	0.0458

Significant α= .05

On average, students who passed the course score had a higher OPREP Midterm examination average by 22 % (78 % compared to 56 %). The two-tailed t-test in Table 4.7 shows that the means of the two groups are statistically significantly different at the 5% confidence level (p-value < 0.0001 < 0.05). The probability of no significant difference between the OPREP Midterm examination average of passing students and failing students is less than 1 in 10,000 (< .0001). They are significantly different whether the investigator assumes that the groups have equal variances – pooled t-test— or unequal variances – Satterthwaite t-test. The folded F statistic shows that the variances are statistically significantly different (unequal) at the 5% level (p-value = 0.0458 < 0.05). The Satterthwaite t-test statistic and degrees of freedom were used to calculate the effect size, Cohen's d. The effect size for a 22-point difference in the average score is 1.48. This is considered large (above 0.8) based on Cohen's standard. An approximate effect size of 1.5 indicates that Midterm examination average score of the passing group, 78 %, is at the 93.3rd percentile of the mean of the failing group, 56 %. The effect size correlation, r_{Y1}, is 0.596. For a Cohen's d value of approximately 1.48, the amount of variance in the dependent variable, Midterm examination, that is accounted by membership in the independent variable, CBT exit examination status, groups (fail and pass) is 35.5 %, r_{Y1}^2.

The number of observations, n = 249, for the non-OPREP Departmental Final and Midterm examinations differs from the number of observations, n = 261, for the OPREP Quiz because no Departmental Final and Midterm examinations were given during the shortened summer semester. If these twelve summer observations are excluded, and the same 249 observations are used for the OPREP Quiz, then the effect size is much larger. The folded F statistic in Table 23 shows that the variances are significantly different (unequal) at the 5% level (p-value = 0.0484 < 0.05). The Satterthwaite t-test statistic and degrees of freedom were used to calculate the effect size, Cohen's d. The effect size for a 32-point difference in the average score is 1.61. An approximate effect size of 1.6 indicates that the Quiz average score of the passing group, 73 %, is at the 94.5th percentile of the mean of the failing group, 40 %. The effect size correlation, r_{Y1}, is 0.627. For a Cohen's d value of approximately 1.61, the amount of variance in the dependent variable, OPREP quiz, that is accounted by membership in the independent variable, CBT exit examination status, groups (fail and pass) is 39.3 %, r_{Y1}^2.

Table 4.7

Two-tailed t-test comparing the OPREP quiz average (n = 249): excludes 12 observations from the summer semester

Variable: Quiz

CBT Exit Exam Status	N	Mean	Std Dev	Std Err	Minimum	Maximum
Pass	198	72.6325	26.2112	1.8627	0	111.1
Fail	51	40.2380	32.2775	4.5198	0	98.0556
Diff (1-2)		32.3945	27.5473	4.3257		

CBT Exit Exam Status	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
Pass		72.6325	68.9590	76.3060	26.2112	23.8588	29.0823
Fail		40.2380	31.1598	49.3162	32.2775	27.0069	40.1235
Diff (1-2)	Pooled	32.3945	23.8745	40.9146	27.5473	25.3174	30.2111
Diff (1-2)	Satterthwaite	32.3945	22.6394	42.1497			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	247	7.49	<.0001
Satterthwaite	Unequal	67.931	6.63	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	50	197	1.52	0.0484

Significant α= .05

Significant α= .05

Table 4.8 summarizes the results of the t-test that compares average scores on the OPREP assignments of students who passed versus students who failed the CBT exit examination. Included in Table 24 are variables related to the time spent and amount of activity while using WebAssign, the OPREP. The last section of includes summative assessments such as a midterm examination and placement/ entrance examinations that were not delivered through WebAssign.

Overall, most of the results in Table 4.8 are highly significant (<< 0.01), but "aggregated time spent" (OPREP Metrics for Time & Activity) was not significant, and "Number of log-ins" was barely significant (p = 0.045). The largest effects were for the Quiz and the non-OPREP examination variables. A large effect size, Cohen's d, by Cohen's standard is 0.8 or above, medium effect size is between 0.8 and 0.5. A small effect size is less than 0.5.

Table 4.8

Summary of t-test results, effect size: Cohen's d and effect size correlation for All Sections

T-test Results, Effect Size: Cohen's d , Effect Size Correlation for All Sections Observations (n= 261)

	Variable	Degrees of Freedom	t-value	p-value	Cohen's d	Cohen's Standard	Effect Size Correlation , r_{Y1}	r_{Y1}^2 (%)
OPREP Assignments	Quiz (n = 249) Summer Excluded	67.931	6.63	< .0001	1.609	**Large**	0.627	39.29%
	Quiz (n = 261)	259	7.72	< .0001	0.959	**Large**	0.433	18.71%
	In Class Assignments Average	259	4.59	< .0001	0.570	Medium	0.274	7.52%
	Homework Average	259	5.46	< .0001	0.679	Medium	0.321	10.32%
	Midterm Practice	247	5.57	< .0001	0.709	Medium	0.334	11.16%
	Cumulative Quiz	161	3.59	0.0004	0.566	Medium	0.272	7.41%
	Practice Final Exam	123	3.82	0.0002	0.689	Medium	0.326	10.61%
	Practice CBT Final	185	4.93	< .0001	0.566	Medium	0.272	7.41%
OPREP Metrics for Time & Activity	Aggregated time spent	259	0.92	0.3581	Not Statistically Significant			
	Aggregated activities	258	3.02	0.0028	0.376	Small	0.185	3.41%
	Aggregated log-in days	259	2.43	0.0159	0.302	Small	0.149	2.23%
	Number of log-ins	152	2.02	0.0452	0.328	Small	0.162	2.61%
	Attendance	259	3.62	0.0004	0.450	Small	0.219	4.82%
Exams (non-OPREP)	Departmental Final Exam	247	8.88	< .0001	1.130	**Large**	0.492	24.20%
	Departmental Midterm Exam	67.839	6.11	< .0001	1.484	**Large**	0.596	35.50%
	Algebra Compass Entrance Exam	115.42	6.41	< .0001	1.193	**Large**	0.512	26.25%
	Pre-Algebra Compass Placement	114.7	5.71	< .0001	1.066	**Large**	0.470	22.13%

Comparisons of CBT exit examination results and type of instruction. All students in the classes receiving the OPREP altered pedagogy technique were taught by the same instructor in different semesters. One potential significant difference was the type of class: Hybrid e-learning, ASAP (Accelerated Study in Associate Programs), and traditional. In this context, ASAP refers to a program designed to increase retention rates and accelerate graduation rates through financial support (e.g., tuition assistance) and academic support (e.g., intrusive advising) services. The urban community college e-learning department defines a course as hybrid if at least 33%-80% of the content is discussed online with the remainder of the content delivered through traditional face-to-face meetings. Regular attendance in both formats is required. For purposes of this discussion the students in the traditional and ASAP block Elementary Algebra sections meet face-to-face twice a week; however, the hybrid sections meet face-to-face once a week. The majority (52%) of the students were enrolled in traditional sections, as shown in Table 4.9.

Table 4.9

Elementary Algebra enrollment by class type

Class Type	Frequency	Percent	Cumulative Frequency	Cumulative Percent
ASAP	54	20.69	54	20.69
Hybrid	71	27.20	125	47.89
Traditional	136	52.11	261	100.00

A natural question to consider is whether there exists a significant performance differences on the CBT exit examination between Elementary Algebra students experiencing different class types. In order to answer this question an Analysis of Variance (Welch ANOVA) test was performed with groups determined by class type. A Welch ANOVA was used because Levene's test showed unequal variances. Tables 4.10 through 4.11 show the results of the Welch ANOVA as well as relevant follow-up tests including a multiple comparison test. Students in the ASAP sections averaged the highest scores, 79 %, on the CBT Final examination, followed by students in the Hybrid sections with an average score of 75%. As seen in Figure 4.11, the students in the traditional sections had the lowest average score, approximately 71%. ANOVA assumes that all groups have similar if not the same variances. In order to test this assumption of homogeneity of variances, Levene's test for homogeneity was performed. As seen in Figure 4.10, the Levene test has a p-value of 0.044, which is less than the critical 0.05 alpha value. This means the null hypothesis of homogenous variances is rejected. Welch's test performs an

ANOVA without the homogeneity of variances assumption. According to Welch's ANOVA, the means of the three groups are statistically significantly different at the 5% confidence level (p-value = 0.0167 < 0.05).

Table 4.10

Results of the ANOVA by class type, Levene's test and Welch's ANOVA

The ANOVA Procedure

Class Level Information		
Class	Levels	Values
Class Type	3	ASAP Hybrid Traditional

Number of Observations Read	261
Number of Observations Used	261

Elementary Algebra CBT Exit Exam ANOVA by Class Type

The ANOVA Procedure

Levene's Test for Homogeneity of CBT Final Exam Variance ANOVA of Squared Deviations from Group Means					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Class Type	2	1105671	552835	3.16	0.0440
Error	258	45096061	174791		

Welch's ANOVA for CBT Final Exam			
Source	DF	F Value	Pr > F
Class Type	2.0000	4.22	0.0167
Error	136.5		

From the the Welch's ANOVA, the class type has statistically significant effect on the average CBT exit examination score at a significance level of 0.05. The Student-Newman-Keuls' (SNK) multiple-range test in Table 27 is a multiple comparison test (post hoc) used to investigte differences in class type groups after the ANOVA global test. (Note. This test controls the Type I experimentwise error rate under the complete null hypothesis but not under the partial null hypothesis.)

Table 4.11

SNK test post hoc ANOVA test comparing difference between the three class type groups

Elementary Algebra CBT Exit Exam ANOVA by Class Type

The ANOVA Procedure

Student-Newman-Keuls Test for CBT Final Exam

Alpha	0.05
Error Degrees of Freedom	258
Error Mean Square	339.1276
Harmonic Mean of Cell Sizes	75.08265

Note: Cell sizes are not equal.

Number of Means	**2**	**3**
Critical Range	5.9185721	7.0850923

Means with the same letter are not significantly different.

SNK Grouping		**Mean**	**N**	**Class Type**
	A	78.667	54	ASAP
	A			
B	A	74.592	71	Hybrid
B				
B		71.176	136	Traditional

In Table 4.11's SNK "grouping" column, class types with the same letter are not significantly different. This means that the average CBT Final examination score of the Hybrid group, approxiamtely 75% , is not signicantly different from the average CBT Final examination score of the ASAP group, approxiamtely 79%. This is because both groups (ASAP and Hybrid) have the letter A under the SNK grouping column. Similarly, the average CBT Final examination score of the Hybrid group, approxiamtely 75% , is not signicantly different from the average CBT Final examination score of the Traditional group, approxiamtely 71%. This is because both groups (Traditional and Hybrid) have the letter B under the SNK grouping column. The statistically significant group difference lies between the ASAP group and the Traditional group, shown by the different letters in the SNK grouping column, A and B respectively. This result led the investigator to revisit the premise of reserch question (3) and the t-test that followed. The null hypothesis of the t-test, that the performance on the OPREP assignments of failing students does not differ from that of passing students by more than what is expected by chance can be filtered/ evaluated by class type (ASAP, Hybrid and Traditional).

Results for students in the ASAP section. Table 4.12 summarizes the t-test results and effect size for the 54 students in the ASAP sections. This includes t-tests that compare averages (OPREP assignments, OPREP Metrics and non-OPREP summative assessments) of students who passed versus students who failed the CBT exit examination. Homework average comparison and Practice Final examination comparison are not significantly different. Homework average was almost significant ($p = 0.060$). All other OPREP assignments are significantly different and all have a large effect size. The assignment category with the largest effect size is the Cumulative Quiz followed by the Quiz and Midterm Practice. No OPREP metrics for time and activity were statistically significant at the 5% level. Number of log-ins was almost significant ($p = 0.068$). When compared to the t-test results for all sections in Table 4.8, the ACT's Algebra Compass and Pre-Algebra Compass examinations are no longer statistically significant. A large effect size, Cohen's d, by Cohen's standard is 0.8 or above, medium effect size is between 0.8 and 0.5. A small effect size is less than 0.5.

Table 4.12

Summary of t-test results, effect size: Cohen's d & effect size correlation for ASAP sections

T-test Results, Effect Size: Cohen's d , Effect Size Correlation for ASAP Sections Observations (n =54)

	Variable	Degrees of Freedom	t-value	p-value	Cohen's d	Cohen's Standard	Effect Size Correlation , r_{Y1}	r_{Y1}^2 (%)
OPREP Assignments	Quiz	52	3.56	0.0008	0.987	Large	0.443	19.60%
	In Class Assignments Average	52	3.43	0.0012	0.951	Large	0.430	18.45%
	Homework Average	52	1.92	0.0599	Not Statistically Significant			
	Midterm Practice	52	3.56	0.0008	0.987	Large	0.443	19.60%
	Cumulative Quiz	32	3.55	0.0012	1.255	Large	0.532	28.26%
	Practice Final Exam	18	1.1	0.285	Not Statistically Significant			
	Practice CBT Final	32	2.43	0.0211	0.859	Large	0.395	15.58%
OPREP Metrics for Time & Activity	Aggregated time spent	52	1.06	0.2943	Not Statistically Significant			
	Aggregated activities	52	1.33	0.1902	Not Statistically Significant			
	Aggregated log-in days	52	1.36	0.1806	Not Statistically Significant			
	Number of log-ins	32	1.89	0.0677	Not Statistically Significant			
	Attendance	3.0959	0.57	0.6088	Not Statistically Significant			
Exams (non-OPREP)	Departmental Final Exam	52	3.79	0.0004	1.051	Large	0.465	21.64%
	Departmental Midterm Exam	52	2.76	0.008	0.765	Medium	0.357	12.78%
	Algebra Compass Entrance Exam	47	1.4	0.1682	Not Statistically Significant			
	Pre-Algebra Compass Placement	47	1	0.3235	Not Statistically Significant			

The departmental Final and Midterm examinations maintain their statistical significance but the effect size of the Midterm examination drops from large to medium. When comparing all section observations to the ASAP sections the amount of variance in the dependent variable, Midterm examination, that is accounted by membership in the independent variable, CBT exit examination status, groups (fail and pass) drops from $r_{Y1}^2 = 35.5$ % to $r_{Y1}^2 = 12.8$ %.

Results for students in the Hybrid sections. Table 4.13 summarizes the t-test results and effect size for the 71 students in the Hybrid sections. This includes t-test that compares averages (OPREP assignments, OPREP Metrics and non-OPREP summative assessments) of students who passed versus students who failed the CBT exit examination. Quiz average comparison and the Midterm Practice examination comparison were the only OPREP assignments that are statistically significantly different and they have medium effect sizes. A large effect size, Cohen's d, by Cohen's standard is 0.8 or above, medium effect size is between 0.8 and 0.5. A small effect size is less than 0.5.

Table 4.13

Summary of t-test results, effect size: Cohen's d & effect size correlation for Hybrid sections

T-test Results, Effect Size: Cohen's d, Effect Size Correlation for Hybrid Sections Observations (n =71)								
	Variable	Degrees of Freedom	t-value	p-value	Cohen's d	Cohen's Standard	Effect Size Correlation , r_{Y1}	r_{Y1}^2 (%)
OPREP Assignments	Quiz	69	2.3	0.0247	0.554	Medium	0.267	7.12%
	In Class Assignments Average	69	1.67	0.0985	Not Statistically Significant			
	Homework Average (Satterthwaite)	15.929	1.89	0.0775	Not Statistically Significant			
	Midterm Practice	57	2.33	0.0234	0.617	Medium	0.295	8.70%
	Cumulative Quiz	31	1.2	0.2383	Not Statistically Significant			
	Practice Final Exam	24	0.53	0.6032	Not Statistically Significant			
	Practice CBT Final	55	1.96	0.0547	Not Statistically Significant			
OPREP Metrics for Time & Activity	Aggregated time spent	69	0.22	0.8287	Not Statistically Significant			
	Aggregated activities	68	2.18	0.0329	0.529	Medium	0.256	6.53%
	Aggregated log-in days	16.08	0.96	0.3503	Not Statistically Significant			
	Number of log-ins	6.6047	0.06	0.9514	Not Statistically Significant			
	Attendance	69	1.32	0.1922	Not Statistically Significant			
Exams (non-OPREP)	Departmental Final Exam	57	4.75	< .0001	1.258	**Large**	0.533	28.36%
	Departmental Midterm Exam	12.348	3.49	0.0043	1.986	**Large**	0.705	49.66%
	Algebra Compass Entrance Exam	32.732	2.95	0.0059	1.031	**Large**	0.458	21.00%
	Pre-Algebra Compass Placement	64	2.51	0.0147	0.628	Medium	0.299	8.96%

When compared to all sections results, the Quiz category dropped from a large effect size to a medium effect size. Homework average (p = 0.078) and Practice CBT Final (p = 0.054) were almost significant. Aggregated activities category is the only OPREP metric for time or activity that is statistically significant at the 5% level and the effect size is medium. All of the summative non-OPREP examinations are still statistically significant and have large effect sizes except for the Pre-Algebra Compass. When compared to the t-test results for all sections in Table 4.8, the effect size of ACT's Pre-Algebra Compass dropped from large to medium. The departmental Midterm examination maintains its statistical significance and large effect size. When comparing all section observations to the traditional sections the amount of variance in the dependent variable, Midterm examination, that is accounted by membership in the independent variable, CBT exit examination status, groups (fail and pass) rises from r_{Y1}^2 = 35.5 % to r_{Y1}^2 = 49.7 %.

For the Homework average category, the folded F statistic in Table 4.14 shows that the variances are significantly different at the 5% level (p-value = 0.0356 < 0.05); however, the Satterthwaite t-value is not significant at the 5% level (p-value = 0.0775 > 0.05). The means are not significantly different.

Table 4.14

Two-tailed t-test comparing the OPREP Homework average (n = 71) of Hybrid sections

Variable: Homework Average

CBT Exit Exam Status	N	Mean	Std Dev	Std Err	Minimum	Maximum
Pass	57	77.9502	20.0502	2.6557	23.6967	100.5
Fail	14	61.9297	30.1744	8.0644	11.5385	98.7500
Diff (1-2)		16.0205	22.3117	6.6552		

CBT Exit Exam Status	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
Pass		77.9502	72.6302	83.2703	20.0502	16.9275	24.5965
Fail		61.9297	44.5076	79.3519	30.1744	21.8750	48.6122
Diff (1-2)	Pooled	16.0205	2.7438	29.2972	22.3117	19.1304	26.7719
Diff (1-2)	Satterthwaite	16.0205	-1.9850	34.0260			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	69	2.41	0.0188
Satterthwaite	Unequal	15.929	1.89	0.0775

Not Significant α=.05

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	13	56	2.26	0.0356

Significant α= .05

Results for students in the traditional sections. Table 4.15 summarizes the effect size and t-test results that compare averages (OPREP assignments, OPREP Metrics and non-OPREP summative assessments) of students who passed versus students who failed the CBT exit examination for the 136 students in the traditional sections of Elementary Algebra. When compared to all sections results, all other OPREP Assignments comparisons maintain their statistical significance but there are some changes in effect size. The Cumulative Quiz category effect size dropped from medium too small while the effect size of Practice Final examination rose from medium too large. The largest effect size is the Practice Final Examination followed by the Quiz and Practice CBT Final. Attendance is the only variable OPREP metric for time and activity categories that is statistically significant at the 5% level and the effect size is medium. Aggregated activities (p = 0.060) and Aggregated log-in days (p = 0.080) were almost significant. When compared to the t-test results for all sections in Table 4.8, all of the summative non-OPREP examinations are still statistically significant but the effect sizes of the Pre-Algebra Compass and Departmental Midterm examinations dropped from large to medium.

Table 4.15

Summary of t-test results, Cohen's d & effect size correlation for traditional sections

T-test Results, Effect Size: Cohen's d, Effect Size Correlation for Traditional Sections Observations (n= 136)

	Variable	Degrees of Freedom	t-value	p-value	Cohen's d	Cohen's Standard	Effect Size Correlation , r_{Y1}	r_{Y1}^2 (%)
OPREP Assignments	Quiz	134	6.58	< .0001	1.137	**Large**	0.494	24.42%
	In Class Assignments Average	134	3.14	0.0021	0.543	Medium	0.262	6.85%
	Homework Average	134	3.73	0.0003	0.644	Medium	0.307	9.41%
	Midterm Practice	134	3.52	0.0006	0.608	Medium	0.291	8.46%
	Cumulative Quiz	94	2.18	0.0319	0.450	Small	0.219	4.81%
	Practice Final Exam	68.148	5.4	< .0001	1.308	**Large**	0.547	29.97%
	Practice CBT Final	94	3.99	0.0001	0.823	**Large**	0.381	14.48%
OPREP Metrics for Time & Activity	Aggregated time spent	134	0.91	0.3625	Not Statistically Significant			
	Aggregated activities	134	1.9	0.0594	Not Statistically Significant			
	Aggregated log-in days	134	1.77	0.0793	Not Statistically Significant			
	Number of log-ins	73	1.64	0.1044	Not Statistically Significant			
	Attendance	134	2.78	0.0061	0.480	Small	0.234	5.45%
Exams (non-OPREP)	Departmental Final Exam	134	5.88	< .0001	1.016	**Large**	0.453	20.51%
	Departmental Midterm Exam	134	3.88	0.0002	0.670	Medium	0.318	10.10%
	Algebra Compass Entrance Exam	81.961	4.9	< .0001	1.082	**Large**	0.476	22.66%
	Pre-Algebra Compass Placement	79.795	3.51	0.0007	0.786	Medium	0.366	13.37%

When comparing all section observations to the traditional sections the amount of variance in the dependent variable, Midterm examination, that is accounted by membership in the independent variable, CBT exit examination status, groups (fail and pass) drops from r_{Y1}^2 = 35.5 % to r_{Y1}^2 = 10.1 %.

Research Question 4: OPREP Assignments as Early Predictors for Student Achievement

4. Can students' average grades on different types of OPREP assignments be used as early predictors for student achievement?

As a result of the significant differences reported in question (3), this next step examines statistical significant relationships between students' grades on OPREP assignments and student achievement (i.e., score on CBT Final examination) through the use of correlation analyses. A correlation matrix was created to identify any highly correlated (greater than 0.4 in absolute value) variables. Once identified, multiple regression analysis was used to determine whether student grades on OPREP assignments could be used as predictors for student achievement. Multiple measures for multiple regression model selection criteria were considered to help determine the most relevant possible independent variables (students' grades on OPREP assignments) and their ability to predict the dependent variables (student achievement measured by score on CBT Final examination). The purpose is to use early indicators on WebAssign assignments to identify Developmental Mathematics students who can benefit from intervention. Important factors such as student demographics were considered when identifying possible patterns in subsets of the population.

Correlation: OPREP assignments and OPREP time/ activity metrics. Table 4.16 is a 17 x 17 correlation matrix of Pearson correlation coefficients for every combination of OPREP assignments, OPREP time and activity metrics and summative assessments. Only statistically significant correlation coefficients greater than 0.3 in absolute value are displayed and duplicated correlation coefficients below the diagonal are not shown. Since the CBT Final examination serves as the exit examination and the score represents a measure of student achievement, row one of the correlation matrix is of vital importance. Student achievement is significantly (α = .05) correlated with several outcomes; every OPREP assignment, OPREP time and activity metric, and Non-OPREP assessment, that were included in this study. All correlations were positive, meaning that increase in student performance on any of these variables should coincide with an increase in CBT final examination score.

All OPREP assignments are statistically significantly correlated with the CBT Final examination at the 1% level and the Pearson correlation coefficients range from 0.403 to 0.536. In general, the OPREP assignments had a stronger relationship to the CBT Final examination than the OPREP time and activity metrics. The placement examinations had higher correlations than the OPREP time and activity metrics but lower than OPREP assignments. The midterm examination had correlation coefficients on par with most OPREP assignments except for the Quiz average. As expected the PDT departmental Final examination had the strongest correlation to the CBT Final examination.

Of all the OPREP assignments, the Quiz average has the highest correlation, $r = 0.536$. With $r^2 = 0.288$, the students' average score on the Quiz accounts for approximately 29% of the variance in the CBT Final examination score.

Table 4.16

17 x 17 Matrix of significant Pearson correlation coefficients (> |0.3|) of OPREP assignments, metrics & assessments

Exit Exam = CBT Final Exam, Class Type = All Sections (n = 261)

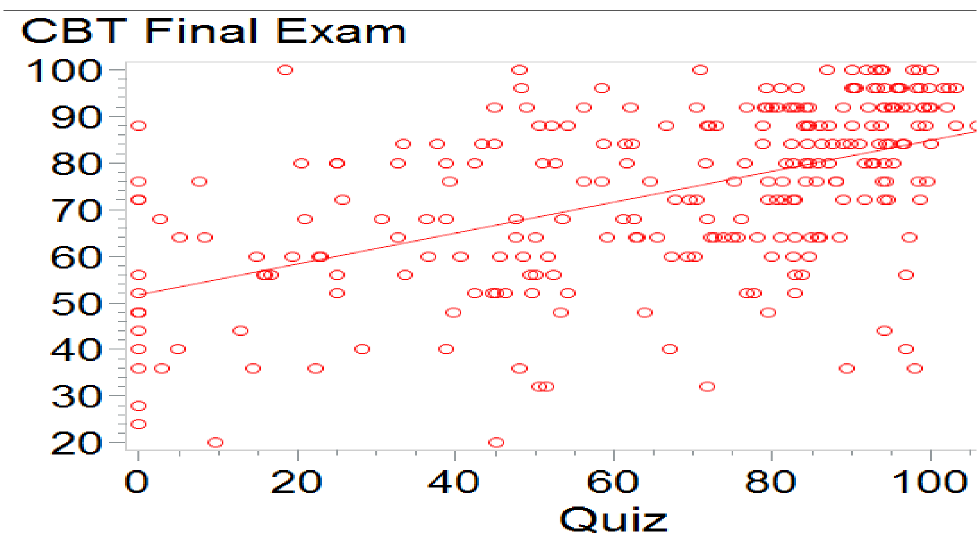
Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

	CBT Final Exam	Departmental Final Exam	Midterm Exam	Quiz	In Class Assignments Average	Homework Average	Midterm Practice	Cumulative Quiz	Practice Final Exam	Practice CBT Final	Aggregated time spent	Aggregated activities	Aggregated log-in days	Number of log-ins	Attendance	Algebra Compass Entrance Exam	Pre-Algebra Compass Placement
CBT Final Exam	1	0.59628	0.4863	0.53625	0.40335	0.43438	0.44454	0.44549	0.48028	0.47731					0.31147	0.3174	0.33935
		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001					<.0001	<.0001	<.0001
	261	249	249	261	261	261	249	163	125	187					261	240	238
Departmental Final Exam		1	0.67668	0.42711	0.47927	0.52635	0.43015	0.57031	0.44575	0.38798				0.33146	0.35319		0.30063
			<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				<.0001	<.0001		<.0001
		249	249	249	249	249	249	163	125	175				142	249		227
Midterm Exam			1	0.37795	0.4412	0.49925	0.41624	0.42024	0.38945	0.27148							0.33338
				<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0003							<.0001
			249	249	249	249	249	163	125	175							227
Quiz				1	0.57189	0.61122	0.58899	0.49307	0.64766	0.49167	0.31498	0.39016	0.38752	0.47533	0.39244		
					<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
				261	261	261	249	163	125	187	261	260	261	154	261		
In Class Assignments Average					1	0.74171	0.48448	0.55914	0.46661	0.32684	0.34546	0.47173	0.38074	0.39956	0.37632		
						<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
					261	261	249	163	125	187	261	260	261	154	261		
Homework Average						1	0.52137	0.6421	0.44869	0.41305	0.3758	0.56966	0.45152	0.46733	0.43647		0.30508
							<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
						261	249	163	125	187	261	260	261	154	261		238
Midterm Practice							1	0.58653	0.58171	0.47125			0.30169	0.34382	0.32202		
								<.0001	<.0001	<.0001			<.0001	<.0001	<.0001		
							249	163	125	175			249	142	249		
Cumulative Quiz								1	0.54707	0.56599	0.33707	0.47936	0.44208	0.44997	0.3631		
									0.0003	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
								163	39	163	163	163	163	142	163		
Practice Final Exam									1	0.73905	0.41399	0.45306	0.46929	0.69524	0.30902		
										<.0001	<.0001	<.0001	<.0001	0.0014	0.0005		
									125	51	125	124	125	18	125		
Practice CBT Final										1	0.30814	0.35775	0.38943	0.4088	0.36405		
											<.0001	<.0001	<.0001	<.0001	<.0001		
										187	187	187	187	154	187		
Aggregated time spent											1	0.64244	0.70376	0.79068			
												<.0001	<.0001	<.0001			
											261	260	261	154			
Aggregated activities												1	0.77981	0.81757	0.35648		
													<.0001	<.0001	<.0001		
												260	260	154	260		
Aggregated log-in days													1	0.98349	0.45051		
														<.0001	<.0001		
													261	154	261		
Number of log-ins														1	0.40093		
															<.0001		
														154	154		
Attendance															1		
															261		
Algebra Compass Entrance Exam																1	0.63038
																	<.0001
																240	238
Pre-Algebra Compass Placement																	1
																	238

Regression analysis of CBT Final examination vs. quiz. Given the significant correlation between CBT final examination scores and the quiz average, a regression analysis was done to examine the relationship. Figure 4.7 illustrates a scatter plot with regression line and regression model of the dependent variable, CBT Final examination, and the independent variable, Quiz.

Figure 4.7

Scatter plot with regression line of CBT Final examination vs Quiz



Scatter plot with Regression Line: CBT Final Exam vs Quiz

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	261
Number of Observations Used	261

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	25808	25808	104.54	<.0001
Error	259	63941	246.87584		
Corrected Total	260	89749			

Root MSE	15.71228	**R-Square**	0.2876
Dependent Mean	73.65517	**Adj R-Sq**	0.2848
Coeff Var	21.33222		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	51.70762	2.35663	21.94	<.0001
Quiz	1	0.33117	0.03239	10.22	<.0001

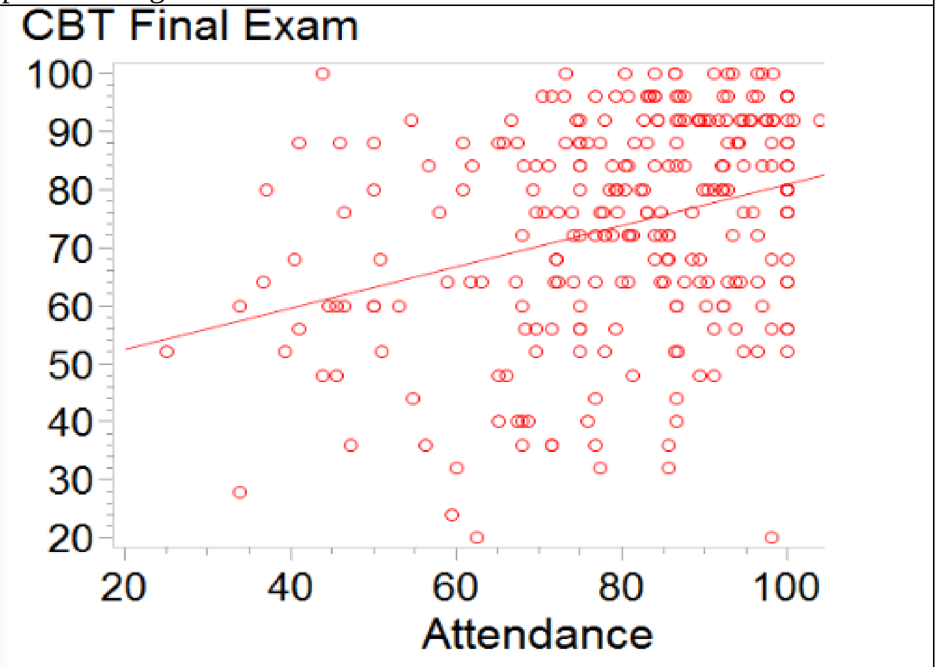
According to Figure 4.7, the linear regression model (slope: M = $b_1 \approx 0.401$ and y-intercept: $b_0 \approx 43.95$) predicts that a 1-point increase in a student's Quiz average results in a 0.331-point increase in the CBT Final examination score.

OPREP metrics correlation with CBT Final examination scores. All OPREP time and activity metrics are significantly correlated with the CBT Final examination at the 5% level and the Pearson correlation coefficients range from 0.137 to 0.311. Of all the OPREP time and activity measures, the Attendance average has the highest correlation, $r = 0.311$. The correlation coefficient and p-value of Attendance variable is the only OPREP time and activity metric displayed in Table 4.17 because it is the only measure (within this subset) with a Pearson correlation coefficient greater than $|0.3|$. With $r^2 = 0.097$, the students average Attendance score accounts for approximately 9.7% of the variance in the CBT Final examination score. Figure 4.8 illustrates a scatter plot with regression line and regression model of the dependent variable, CBT Final examination, and the independent variable, Attendance.

There is considerable scatter of points in the range of 60 to ~ 80 for the attendance data (abscissa). However, there is more tightening of the plotted points for the higher attendance rates. In general, the CBT Final examination score increases as a student's attendance increases but the relationship is not strong. The broad scatter of the points is not particularly unexpected because attendance can be affected by a multitude of variables, that are not entirely related to the student's academic ability, motivation, or other contributing variables expected to affect academic performance (e.g., CBT Final Exam score). Nonetheless, a lack of attendance in a course at some point clearly must compromise the student's academic achievement, especially in highly specialized subject content that is not easily obtained from other sources outside of class.

Figure 4.8

Scatter plot with regression line of CBT Final examination vs Attendance



Scatter plot with Regression Line: CBT Final Exam vs Attendance

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	261
Number of Observations Used	261

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	8706.84263	8706.84263	27.83	<.0001
Error	259	81042	312.90395		
Corrected Total	260	89749			

Root MSE	17.68909	R-Square	0.0970
Dependent Mean	73.65517	Adj R-Sq	0.0935
Coeff Var	24.01609		

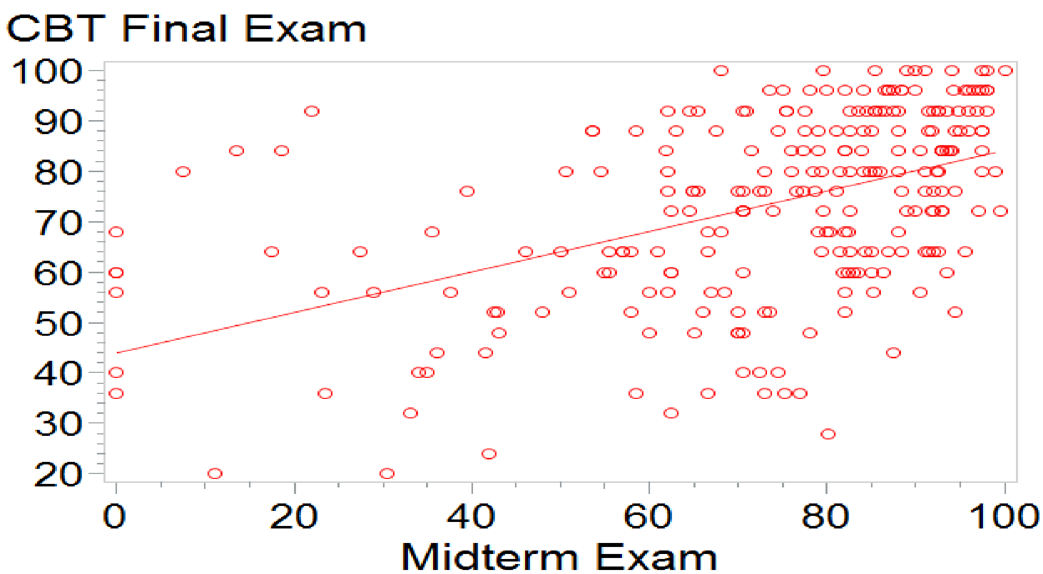
Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	45.31581	5.48280	8.27	<.0001
Attendance	1	0.35557	0.06741	5.28	<.0001

Non-OPREP summative assessments and Compass placement relationships. All non-OPREP summative assessments including the Pre-Algebra and Algebra ACT Compass placement are significantly correlated with the CBT Final examination at the 1% level and the Pearson correlation coefficients range from 0.317 to 0.596. Of all non-OPREP summative assessments, the Departmental Final examination score has the highest correlation coefficient, r = 0.596. However, Departmental Final examination score is not considered an early indicator that could be used to predict the CBT Final examination score because the two examinations are administered at the end of the semester within two weeks of each other. The Midterm examination score can be an early indicator and has the second highest correlation coefficient, r = 0.486, of all the summative assessments. Figure 4.9 depicts a scatter plot with regression line and regression model of the dependent variable, CBT Final examination, and the independent variable, Midterm examination. With $r^2 = 0.237$, the student score on the Midterm examination accounts for approximately 24% of the variance in the CBT Final examination score. It should be noted that students' average score on the OPREP Quiz accounted for a higher percentage of the variance in the CBT Final examination, 29%, than the Midterm examination, 24%. According to Figure 15, the linear regression model (slope: $M = b_1 \approx 0.401$ and y-intercept: $b_0 \approx 43.95$) predicts that a 1-point increase in a student's Midterm score results in a 0.401-point increase in the CBT Final examination score.

It is interesting to note, that overall there appears to be a much tighter plot of the points around the regression line for the prediction of CBT Final Exam scores based on the Midterm Examination scores compared to the scatter of points in the plot of attendance effects on the CBT Final Examination score; again likely because the Midterm Examination is a more robust predictor for cumulative student achievement. There is a much stronger positive relationship between the summative assessments.

Figure 4.9

Scatter plot with regression line of CBT Final examination vs Midterm



Scatter plot with Regression Line: CBT Final Exam vs Midterm Exam

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	261
Number of Observations Used	249
Number of Observations with Missing Values	12

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	20069	20069	76.50	<.0001
Error	247	64795	262.32855		
Corrected Total	248	84864			

Root MSE	16.19656	R-Square	0.2365
Dependent Mean	73.47791	Adj R-Sq	0.2334
Coeff Var	22.04276		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	43.95466	3.52800	12.46	<.0001
Midterm Exam	1	0.40132	0.04588	8.75	<.0001

It is important to note that three OPREP assignments and one OPREP time and activity metric have a significantly reduced number of observations when compared to the maximum, n = 261. In terms of OPREP assignments, the Cumulative Quiz (n = 163), Practice Final Examination (n = 125) and Practice CBT Examination (n = 187) have been between 48% to 72% of the maximum number of observations. The Number of log-ins (n = 154) has at most 59% of the maximum number of observations. In order to maximize the statistical power of the test of statistical significance, the remaining quantitative methods will increase test sensitivity by maximizing the number of observations used. Therefore, the four variables mentioned above were dropped from consideration in the remaining analysis. The Cumulative Quiz, Practice Final examination and Practice CBT examination are late semester assignments so they theoretically would not function as early predictors of student achievement. Also, the Number of log-ins and the Aggregated log-in days are highly correlated, r = 0.98349; theoretical the only difference is that the Number of log-ins includes multiple log-ins each day. Table 4.17 is a 13 by 13 correlation matrix of Pearson correlation coefficients for every combination of the remaining OPREP assignments, OPREP time and activity metrics and summative assessments.

All variables with displayed correlation coefficients in row one of Table 4.17 are statistically significantly correlated with the CBT Final examination at the 1% level and the Pearson correlation coefficients range from 0.311 to 0.596. Specifically, OPREP assignments are statistically significantly correlated with the CBT Final examination at the 1% level and the Pearson correlation coefficients range from 0.403 to 0.536. Once again, of all the OPREP assignments, the Quiz average has the highest correlation, r = 0.536. With $r^2 = 0.288$, the students' average score on the Quiz accounts for approximately 29% of the variance in the CBT Final examination score.

Table 4.17

13 x 13 Matrix of significant Pearson correlation coefficients (> |0.3|) of OPREP assignments, metrics & assessments

Exit Exam = CBT Final Exam, Class Type = All Sections (n = 261)

Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

	CBT Final Exam	Departmental Final Exam	Midterm Exam	Quiz	In Class Assignments Average	Homework Average	Midterm Practice	Aggregated time spent	Aggregated activities	Aggregated log-in days	Attendance	Algebra Compass Entrance Exam	Pre-Algebra Compass Placement
CBT Final Exam	1	0.59628	0.4863	0.53625	0.40335	0.43438	0.44454				0.31147	0.3174	0.33935
		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				<.0001	<.0001	<.0001
	261	249	249	261	261	261	249				261	240	238
Departmental Final Exam		1	0.67668	0.42711	0.47927	0.52635	0.43015				0.35319		0.30063
			<.0001	<.0001	<.0001	<.0001	<.0001				<.0001		<.0001
		249	249	249	249	249	249				249		227
Midterm Exam			1	0.37795	0.4412	0.49925	0.41624						0.33338
				<.0001	<.0001	<.0001	<.0001						<.0001
			249	249	249	249	249						227
Quiz				1	0.57189	0.61122	0.58899	0.31498	0.39016	0.38752	0.39244		
					<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
				261	261	261	249	261	260	261	261		
In Class Assignments Average					1	0.74171	0.48448	0.34546	0.47173	0.38074	0.37632		
						<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
					261	261	249	261	260	261	261		
Homework Average						1	0.52137	0.3758	0.56966	0.45152	0.43647		0.30508
							<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
						261	249	261	260	261	261		238
Midterm Practice							1			0.30169	0.32202		
										<.0001	<.0001		
							249			249	249		
Aggregated time spent								1	0.64244	0.70376			
									<.0001	<.0001			
								261	260	261			
Aggregated activities									1	0.77981	0.35648		
										<.0001	<.0001		
									260	260	260		
Aggregated log-in days										1	0.45051		
											<.0001		
										261	261		
Attendance											1		
											261		
Algebra Compass Entrance Exam												1	0.63038
													<.0001
												240	238
Pre-Algebra Compass Placement													1
													238

Multiple Linear Regression Model: All Class Types

Multiple linear regression analysis was used to determine what group of independent variables served as the best set of predictors for the CBT Final examination, the dependent variable. The Schwartz Baysian Criterion (SBC), an information criteria measure, was used to determine the best subset of predictors. The investigator used SAS to calculate the beta coeffiecients as well as the relevant model selection measures – SBC, Baysian Information Criterion (BIC), Akaike Information Criterion (AIC), Root Mean Square Error (RMSE), Mallows CP (CP), R-squared (R^2) and Adjusted R-squared – for different subsets of predictors. These different models were sorted by SBC from lowest to highest. The SBC column of Table 34 depicts the best model based on minimizing SBC.

Like other information criteria measures (i.e., AIC, BIC), the model with the lowest SBC is consider closest to the true underlying model. It is important to note that models without an intercept, b_0, were excluded from consideration because there was no solid theoretical basis to conclude that the intercept was 0. The model that minimized SBC included the following predictors: Quiz , Midterm Practice examination, Midterm Exam, Pre-Algebra Compass Placement examination, Freshman (Freshman= 1, Sophmore= 0), Hispanic, SeasonF (Fall = 1, Spring = 0), ClassTypeA (ASAP= 1, Not ASAP = 0). Only six of the eight predictors are significant at the 5% level. The Freshman variable, which represents class standing, has a p-value of 0.1111 and the ClassTypeA variable, which represents ASAP sections, has a p-value of 0.0645.

In order to modify the best SBC model into a model with significant predictors, the investigator employed the heuristic statistical technique of backward elimination. The result is depicted in Table 4.18 under the SBC + Backward column. The multiple linear regresssion model started with the eight predictors from the minimized SBC model and systematically removed, one step at a time, the insignificant variables with p-values greater than 0.05.

Table 4.18

Best Multiple Linear Regression model by SBC Information Criteria Measure: All Sections

	Dependent Variable: 'CBT Final Exam'n					
	All Sections					
	Heuristic		Information Criteria			
Model Selection Measures:	Max Obs Heuristic	p-value	SBC	p-value	SBC + Backward	p-value
Schwartz Baysian Criterion (SBC):	1225.539		1231.162		1225.539	
Baysian Information Criterion (BIC):	1203.745		1202.991		1203.745	
Akaike Information Criterion (AIC):	1201.503		1200.258		1201.503	
Root Mean Square Error (RMSE):	13.576		13.483		13.576	
Mallows CP (CP):	10.096		9.000		10.096	
R-squared (R^2):	**0.451**		0.464		**0.451**	
Number of Observation Read:	261		261		261	
Number of Observation Used:	229	Max Obs	229		229	Max Obs
Independent Variables / Predictors						
Intercept	32.1378	<.0001	34.5361	<.0001	32.1378	<.0001
In Class Assignments Average						
Homework Average						
Quiz	0.1939	<.0001	0.1910	<.0001	0.1939	<.0001
Midterm Practice	0.0731	0.0238	0.0706	0.0319	0.0731	0.0238
Aggregated time spent						
Aggregated activities						
Aggregated log-in days						
Attendance						
Midterm Exam	0.2486	<.0001	0.2537	<.0001	0.2486	<.0001
Algebra Compass Entrance Exam						
Pre-Algebra Compass Placement	0.2190	<.0001	0.2238	<.0001	0.2190	<.0001
Freshman (Freshman=1, Sophmore=0)			**~~-3.5498~~**	**~~0.1111~~**		
Female (Female =1, Male =0)						
Black						
Hispanic	5.2856	0.0047	5.0872	0.0062	5.2856	0.0047
Asian						
NHWhite (Non-Hispanic White)						
LSES (Low Socioeconomic Status)						
SeasonF (Fall = 1, Spring = 0)	-7.1805	0.0002	-8.6770	<.0001	-7.1805	0.0002
ClassTimeM (Morning = 1, Afternoon = 0)						
ClassTypeA (ASAP= 1, Not ASAP = 0)			**~~4.7052~~**	**~~0.0645~~**		
ClassTypeH (Hybrid= 1, Not Hybrid = 0)						

Note. Highlighted columns converge to the same model. Independent variables that are not significant at the 5% level are identified by beta and correponding p-values in bold.

The beta and corresponding p-values were recalculated for each step of the backward elimination. Table 4.19 displays this modified SBC with backward elimination as well as summary of the insignificant variables removed during the elimination process.

Table 4.19

Multiple Linear Regression model by SBC after Backward Elimination: All Sections

Summary of Backward Elimination

Step	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Freshman	7	0.0062	0.4573	9.5595	2.56	0.1111
2	ClassTypeA	6	0.0062	0.4511	10.0965	2.52	0.1139

Heuristic Backward CBT Best Model w/ Demo by SBC w/ Midterm All

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	261
Number of Observations Used	229
Number of Observations with Missing Values	32

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	33625	5604.12143	30.41	<.0001
Error	222	40918	184.31506		
Corrected Total	228	74543			

Root MSE	13.57627	R-Square	0.4511
Dependent Mean	73.44978	Adj R-Sq	0.4362
Coeff Var	18.48374		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Type II SS	Standardized Estimate
Intercept	1	32.13778	3.81248	8.43	<.0001	13097	0
Midterm Exam	1	0.24856	0.04581	5.43	<.0001	5426.24432	0.30560
Quiz	1	0.19386	0.03611	5.37	<.0001	5313.08244	0.32698
Midterm Practice	1	0.07311	0.03211	2.28	0.0238	955.39846	0.14277
SeasonF	1	-7.18049	1.89020	-3.80	0.0002	2659.82334	-0.19716
Pre-Algebra Compass Placement	1	0.21900	0.05142	4.26	<.0001	3343.84746	0.22047
Hispanic	1	5.28559	1.85089	2.86	0.0047	1503.09928	0.14530

Table 4.18 also shows that when both the heuristc backward elimination and the heuristic stepwise elimination are used to identify the best model, both methods converge to the same subset of predictors as the SBC with backward elimination model. The difference in the number of observations (from n = 229 to n = 213) in Table 4.18 is due to the heuristic model procedures removing observations with missing values for any variable. When the same number of observations is used, all three models are the same. Once the predictors are identified using the SBC with backward elimination , the stepwise elimination and the backward elimination have identical beta and p-values as seen in the Max Obs Heuristic and SBC + Backward columns in

Table 4.18. The forward elimination results in a different model with almost all the same predictors except it includes the Algebra Compass Entrance Exam even though not siginificant at the 5% level (p-value 0.3003 > 0.05).

The best model detailed in Table 4.19 accounts for approxiamtely 45%, r-squared = 0.4511, of the variance in the dependent variable, CBT Final examination. In order to further elaborate on the model it is expressed in equation form:

$$CBT\ Final\ Exam = 0.1939 * Quiz + 0.0731 * Midterm\ Practice + 0.2486 * Midterm\ Exam + 0.219 * PreAlg.Compass + 5.2856 * Hispanic - 7.1805 * SeasonF + 32.1378.$$

The two significant demographic predictors were Hispanic and SeasonF. According to this model, Hispanic students, who account for approxiamtely 44% of the observations, score approximately 5.29 points higher than non-Hispanic students. The SeasonF variable indicates that students in the fall semester score approxiamtely 7.18 points lower than students in the spring. According to the model, the most impactful OPREP assignment was the Quiz. A 1 point increase in Quiz average yields a 0.19 point increase in the CBT Final examination score (total possible score = 100). The most impactful non-OPREP assignment was the Midterm Exam. A 1 point increase in Midterm examination score yields approxiamtely a 0.25 point increase in the CBT Final examination score.

Table 4.20 provides a snapshot of the predictions made by the model. Of the 261 observations (students quantitative information), 32 observations were not used because of missing values. Of the 229 remaining observations, the model correctly predicted the passing status of 86% (196/229) of the students who took the CBT Final examination. The remaining 14% respresents the 33 incorrectly predicted students' passing status.

Table 4.20

Snapshot of Model Predictions: All Sections (n =261)

$$\boldsymbol{Model}:\ \ CBT\ Final\ Exam = 0.1939 * \mathrm{Quiz} + 0.0731 * \mathrm{Midterm\ Practice} + 0.2486 * \mathrm{Midterm\ Exam} + 0.219 * \mathrm{PreAlg.Compass} + 5.2856 * \mathrm{Hispanic} - 7.1805 * \mathrm{SeasonF} + 32.1378$$

Output Statistics

Obs	Dependent Variable	Predicted Value	Std Error Mean Predict	Residual	Std Error Residual	Student Residual	Cook's D	Actual Status	Predicted Status
1	76	79.4991	1.6669	-3.4991	13.474	-0.26	0	Pass	Pass
2	92	85.3983	2.1098	6.6017	13.411	0.492	0.001	Pass	Pass
3	84	75.8894	2.4288	8.1106	13.357	0.607	0.002	Pass	Pass
4	64	78.8242	1.952	-14.8242	13.435	-1.103	0.004	Pass	Pass
5	96	81.0823	1.6131	14.9177	13.48	1.107	0.003	Pass	Pass
6	84	86.7827	1.881	-2.7827	13.445	-0.207	0	Pass	Pass
7	84	78.6362	2.0469	5.3638	13.421	0.4	0.001	Pass	Pass
8	92	68.7157	2.3102	23.2843	13.378	1.74	0.013	Pass	Pass
9	72	66.4394	1.8629	5.5606	13.448	0.413	0	Pass	Pass
10	68	64.0129	2.2597	3.9871	13.387	0.298	0	Pass	Pass
14	92	90.0768	2.197	1.9232	13.397	0.144	0	Pass	Pass
18	100	94.4154	2.8206	5.5846	13.28	0.421	0.001	Pass	Pass
19	56	51.9307	2.7996	4.0693	13.284	0.306	0.001	Fail	Fail
20	96	72.2623	1.9842	23.7377	13.43	1.767	0.01	Pass	Pass
21	56	61.095	2.1037	-5.095	13.412	-0.38	0.001	Fail	Pass
22	100	99.9726	3.0183	0.0274	13.237	0.002	0	Pass	Pass
97	80	80.4374	2.1616	-0.4374	13.403	-0.033	0	Pass	Pass
98	92	92.7458	2.2757	-0.7458	13.384	-0.056	0	Pass	Pass
99	64	51.4473	3.1863	12.5527	13.197	0.951	0.008	Pass	Fail
100	84	69.0623	2.709	14.9377	13.303	1.123	0.007	Pass	Pass
101	92	92.4263	2.5617	-0.4263	13.332	-0.032	0	Pass	Pass
151	84	89.2157	2.3231	-5.2157	13.376	-0.39	0.001	Pass	Pass
152	88	86.9725	2.1801	1.0275	13.4	0.077	0	Pass	Pass
153	64	64.0207	2.6004	-0.0207	13.325	-0.002	0	Pass	Pass
154	88	84.3984	2.121	3.6016	13.41	0.269	0	Pass	Pass
155	76	75.3807	1.9155	0.6193	13.44	0.046	0	Pass	Pass
241	84	82.3159	1.7393	1.6841	13.464	0.125	0	Pass	Pass
242	84	76.6076	2.1255	7.3924	13.409	0.551	0.001	Pass	Pass
243	32	62.0258	1.9501	-30.0258	13.435	-2.235	0.015	Fail	Pass
251	76	80.911	1.5906	-4.911	13.483	-0.364	0	Pass	Pass
252	76	75.2267	2.398	0.7733	13.363	0.058	0	Pass	Pass
253	76	68.1941	3.1089	7.8059	13.216	0.591	0.003	Pass	Pass
254	36	65.3338	2.4441	-29.3338	13.354	-2.197	0.023	Fail	Pass
255	96	94.5624	2.4661	1.4376	13.35	0.108	0	Pass	Pass
260	36	49.9984	2.6542	-13.9984	13.314	-1.051	0.006	Fail	Fail
261	60	58.1938	2.2233	1.8062	13.393	0.135	0	Pass	Fail

Sum of Residuals	0
Sum of Squared Residuals	40918
Predicted Residual SS (PRESS)	43733

Two thirds (22/33) of the incorrect projections predicted that students would pass but they failed (see observations 21, 243 and 254 in Figure 43). Examples of the remaining one third (11/33) of the students who were projected to fail but they passed, can be seen in observation 99 and 261 in Table 4.20. In aggregate, 184 students (approximately 80%) passed the CBT Final examination. The model overpredicted the *number* of students passing by projecting 195 (approximately 85%).

Multiple Linear Regression Model: Traditional Sections

Best regression model for different class types. A natural question to consider is whether there exist different best multiple linear regression models for different class types. The ANOVA, Levene's test and Welch's ANOVA in Table 4.10 as well as the SNK multiple-range test in Table 4.11 confirmed that differences in the CBT Final examination performances exist between different class types. The SBC column of Table 4.21 depicts the best model based on minimizing SBC for the traditional class-type. This model included the following predictors: Quiz , Midterm Exam, Algebra Compass Placement examination, Pre-Algebra Compass Placement examination, Freshman (Freshman= 1, Sophmore= 0), Hispanic, Non-Hispanic White and SeasonF (Fall = 1, Spring = 0). All eight predictors are significant at the 5% level. Table 37 also shows that when the investigator, in the prior illustration, used the heuristc approaches to identify the best model, the stepwise elimination and forward eliminations converge to the same model and accounted for 58%, r-squared = 0.581, of the variance in the CBT Final examination score. However, the backward elimination model accounted for 62%, r-squared = 0.621, of the variance. With closer examination, when the same number of observations (n = 124) are used, then the backward elimination model and the SBC model converge to the same subset of predictors with identical beta and p-values as seen in the Max Obs Heuristic and SBC columns in Table 37.

Table 4.21

Best Multiple Linear Regression model by SBC Information Criteria Measure: Traditional

	Dependent Variable: 'CBT Final Exam'n							
	Traditional Sections							
	Heuristic						Information Criteria	
Model Selection Measures:	Backward	p-value	Stepwise	p-value	Max Obs Heuristic	p-value	SBC	p-value
Schwartz Baysian Criterion (SBC):	605.841		607.916		662.217		662.217	
Baysian Information Criterion (BIC):	585.363		590.950		640.231		640.231	
Akaike Information Criterion (AIC):	581.137		588.702		636.835		636.835	
Root Mean Square Error (RMSE):	12.051		12.555		12.591		12.591	
Mallows CP (CP):	5.183		11.994		9.000		9.000	
R-squared (R^2):	0.621		0.581		**0.597**		**0.597**	
Number of Observation Read:	136		136		136		136	
Number of Observation Used:	115		115		124	Max Obs	124	Max Obs
Independent Variables / Predictors								
Intercept	24.7656	<.0001	31.8623	<.0001	24.4877	<.0001	24.4877	<.0001
In Class Assigments Average								
Homework Average								
Quiz	0.3421	<.0001	0.3261	<.0001	0.3214	<.0001	0.3214	<.0001
Midterm Practice								
Aggregated time spent								
Aggregated activities								
Aggregated log-in days								
Attendance								
Midterm Exam	0.1535	0.0050	0.1625	0.0035	0.1748	0.0020	0.1748	0.0020
Algebra Compass Entrance Exam	0.6995	0.0137	0.9310	0.0002	0.5795	0.0364	0.5795	0.0364
Pre-Algebra Compass Placement	0.1875	0.0381			0.2576	0.0036	0.2576	0.0036
Freshman (Freshman=1, Sophmore=0)	-8.9278	0.0011	-7.2742	0.0008	-8.0989	0.0036	-8.0989	0.0036
Female (Female =1, Male =0)								
Black			-6.3514	0.0139				
Hispanic	7.1400	0.0041			7.4297	0.0028	7.4297	0.0028
Asian								
NHWhite (Non-Hispanic White)	14.8570	0.0010			15.1111	0.0010	15.1111	0.0010
LSES (Low Socioeconomic Status)								
SeasonF (Fall = 1, Spring = 0)	-11.0994	<.0001	-10.3235	<.0001	-12.3963	<.0001	-12.3963	<.0001
ClassTimeM (Morning = 1, Afternoon = 0)								

Note. Highlighted columns converge to the same model. Independent variables that are not significant at the 5% level are identified by beta and correponding p-values in bold.

The best model for traditional sections detailed in Table 4.21 accounts for approxiamtely 60%, r-squared = 0.597, of the variance in the dependent variable, CBT Final examination. Table 38 displays the SBC model as well as a summary of model diagnostic measures.

Table 4.22

Multiple Linear Regression SBC model: Traditional Sections

CBT Best Model w/ Demo by SBC w/ Midterm by Type: Traditional

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	136
Number of Observations Used	124
Number of Observations with Missing Values	12

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	27061	3382.57890	21.34	<.0001
Error	115	18231	158.53140		
Corrected Total	123	45292			

Root MSE	12.59093	R-Square	0.5975
Dependent Mean	71.25806	Adj R-Sq	0.5695
Coeff Var	17.66947		

Parameter Estimates							
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Type II SS	Standardized Estimate
Intercept	1	24.48772	5.42060	4.52	<.0001	3235.32463	0
Midterm Exam	1	0.17476	0.05529	3.16	0.0020	1584.03071	0.21637
Quiz	1	0.32135	0.03922	8.19	<.0001	10645	0.52960
SeasonF	1	-12.39628	2.39163	-5.18	<.0001	4259.00605	-0.32224
Freshman	1	-8.09889	2.72054	-2.98	0.0036	1404.93287	-0.19074
Pre-Algebra Compass Placement	1	0.25763	0.08658	2.98	0.0036	1403.63321	0.22034
Algebra Compass Entrance Exam	1	0.57948	0.27372	2.12	0.0364	710.49397	0.16315
Hispanic	1	7.42967	2.43529	3.05	0.0028	1475.54841	0.19374
NHWhite	1	15.11109	4.47716	3.38	0.0010	1805.93193	0.21529

In order to further elaborate on the model for traditional sections it is expressed in equation form:

$$CBT\ Final\ Exam = \ 0.3214 * \mathrm{Quiz} \ + \ 0.1748 * \mathrm{Midterm\ Exam} + 0.5795 *$$

$$\mathrm{Alg.Compass} + 0.2576 * \mathrm{PreAlg.Compass} - 8.0989 * \mathrm{Freshman} + \ 7.4297 *$$

$$\mathrm{Hispanic} + 15.1111 * \mathrm{NHWhite} \ - 12.3963 * \mathrm{SeasonF} \ + 24.4877$$

There are four significant demographic predictors: Freshman, Hispanic, NHWhite and SeasonF. According to this model, freshman score approximately 8.1 points lower than sophmores. Freshmen represent an estimated 72% of the traditional sections' population. Hispanic students, who account for an estimated 47% of the traditional sections' population , score approximately 7.4 points higher than non-Hispanic students as a whole. A beta value of 15.1111 for the NHWhite indicates that non-Hispanic White students, who account for an estimated 8% of the traditional sections' population, score approximately 15.1 points higher than their counterparts. The SeasonF variable indicates that students in the fall semester score approxiamtely 12.4 points lower than students in the spring. According to the model, the only impactful OPREP assignment was the Quiz. A 1 point increase in Quiz average yields a 0.32 point increase in the CBT Final examination score. The most impactful non-OPREP assignment was the Midterm Exam. A 1 point increase in Midterm examination score yields approxiamtely a 0.17 point increase in the CBT Final examination score. Each additional point on the Algebra Compass placement examination results in 0.58 point increase in the CBT Final examination score.

Table 4.23 provides a snapshot of the predictions made by the model. Of the 136 observations, 12 observations were not used because of missing values. Of the 124 remaining observations, the model correctly predicted the passing status of 90% (111/124) of the students who took the CBT Final examination. The remaining 10% respresents the 13 incorrectly predicted students' passing status. Eight of the 13 incorrect projections predicted that students would pass when, in fact, they failed (see observations 25 and 61 in Table 4.23). Examples of the remaining five of the 13, students who were projected to fail but passed, can be seen in observation 136 in Table 4.23. In aggregate, 94 students (approximately 76%) passed the CBT Final examination. The model slightly overpredicted the number of students passing by projecting 97 (approximately 78%).

Table 4.23

Snapshot of Model Predictions: Traditional Sections (n =136)

$$\boldsymbol{Model}:\ \mathit{CBT\ Final\ Exam} = 0.3214 * \text{Quiz} + 0.1748 * \text{Midterm Exam} + 0.5795 * \text{Alg.Compass} + 0.2576 * \text{PreAlg.Compass} - 8.0989 * \text{Freshman} + 7.4297 * \text{Hispanic} + 15.1111 * \text{NHWhite} - 12.3963 * \text{SeasonF} + 24.4877$$

Output Statistics

Obs	Actual Value (Dependent Variable)	Predicted Value	Std Error Mean Predict	Residual	Std Error Residual	Student Residual	Cook's D	Actual Status	Predicted Status
2	76	76.56	2.6898	-0.56	12.3	-0.046	0	Pass	Pass
3	68	73.797	2.0896	-5.797	12.416	-0.467	0.001	Pass	Pass
4	92	70.2741	4.2334	21.7259	11.858	1.832	0.048	Pass	Pass
5	96	98.1098	3.5358	-2.1098	12.084	-0.175	0	Pass	Pass
6	88	92.4418	2.7713	-4.4418	12.282	-0.362	0.001	Pass	Pass
18	92	96.1975	2.7658	-4.1975	12.283	-0.342	0.001	Pass	Pass
19	76	76.4392	4.7895	-0.4392	11.644	-0.038	0	Pass	Pass
25	52	65.3388	2.6836	-13.3388	12.302	-1.084	0.006	Fail	Pass
26	84	93.2924	3.8599	-9.2924	11.985	-0.775	0.007	Pass	Pass
27	88	83.9688	2.597	4.0312	12.32	0.327	0.001	Pass	Pass
28	64	63.2214	3.1856	0.7786	12.181	0.064	0	Pass	Pass
29	88	91.0224	3.1274	-3.0224	12.196	-0.248	0	Pass	Pass
32	64	77.9554	2.5334	-13.9554	12.333	-1.132	0.006	Pass	Pass
33	40	43.6225	3.3887	-3.6225	12.126	-0.299	0.001	Fail	Fail
60	32	41.3827	3.3435	-9.3827	12.139	-0.773	0.005	Fail	Fail
61	52	60.6541	3.306	-8.6541	12.149	-0.712	0.004	Fail	Pass
62	72	73.6331	4.2419	-1.6331	11.855	-0.138	0	Pass	Pass
63	80	78.3684	3.0072	1.6316	12.227	0.133	0	Pass	Pass
72	72	56.0103	3.0073	15.9897	12.227	1.308	0.011	Pass	Fail
89	56	46.4698	3.7927	9.5302	12.006	0.794	0.007	Fail	Fail
90	72	72.04	4.5867	-0.04	11.726	-0.003	0	Pass	Pass
91	48	50.2563	3.1218	-2.2563	12.198	-0.185	0	Fail	Fail
92	88	76.1473	2.4304	11.8527	12.354	0.959	0.004	Pass	Pass
106	28	47.8895	3.9309	-19.8895	11.962	-1.663	0.033	Fail	Fail
107	64	73.7548	2.9224	-9.7548	12.247	-0.796	0.004	Pass	Pass
108	60	60.3405	2.9456	-0.3405	12.242	-0.028	0	Pass	Pass
109	44	43.1295	3.6921	0.8705	12.037	0.072	0	Fail	Fail
120	64	64.0336	2.8079	-0.0336	12.274	-0.003	0	Pass	Pass
121	52	50.4787	2.7154	1.5213	12.295	0.124	0	Fail	Fail
122	76	80.0072	3.5649	-4.0072	12.076	-0.332	0.001	Pass	Pass
133	84	80.0396	4.8285	3.9604	11.628	0.341	0.002	Pass	Pass
134	36	38.4241	3.4426	-2.4241	12.111	-0.2	0	Fail	Fail
135	36	39.8664	3.9181	-3.8664	11.966	-0.323	0.001	Fail	Fail
136	60	46.5336	3.539	13.4664	12.083	1.114	0.012	Pass	Fail

Sum of Residuals	0
Sum of Squared Residuals	18231
Predicted Residual SS (PRESS)	21156

Multiple Linear Regression Model: Hybrid Sections

The SBC column of Table 4.24 depicts the best model based on minimizing SBC for the hybrid class type. The model that minimized SBC included the following predictors: Quiz , Midterm Exam, Algebra Compass Placement examination, Pre-Algebra Compass Placement examination, Female (Female =1, Male =0) and Black. Only four of the six predictors are significant at the 5% level. The Algebra Compass Placement examination variable has a p-value of 0.3384 and the Black variable has a p-value of 0.1197.

Table 4.24

Best Multiple Linear Regression model by SBC Information Criteria Measure: Hybrid

	Dependent Variable: 'CBT Final Exam'n							
	Hybrid Sections							
	Heuristic				Information Criteria			
Model Selection Measures:	Stepwise	p-value	Max Obs Heuristic	p-value	SBC	p-value	Max Obs + SBC + Backward	p-value
Schwartz Baysian Criterion (SBC):	266.313		292.596		293.386		292.596	
Baysian Information Criterion (BIC):	261.025		285.540		283.503		285.540	
Akaike Information Criterion (AIC):	256.753		282.560		279.463		282.560	
Root Mean Square Error (RMSE):	12.431		12.497		12.521		12.497	
Mallows CP (CP):	0.368		5.000		7.000		5.000	
R-squared (R^2):	0.573		**0.555**		0.579		**0.555**	
Number of Observation Read:	71		71		71		71	
Number of Observation Used:	50		55	Max Obs	54		55	Max Obs
Independent Variables / Predictors								
Intercept	18.2494	0.0196	17.6743	0.0211	21.1493	0.0123	17.6743	0.0211
In Class Assigments Average								
Homework Average								
Quiz	0.1443	0.0175	0.1751	0.0024	0.1899	0.0015	0.1751	0.0024
Midterm Practice								
Aggregated time spent								
Aggregated activities								
Aggregated log-in days								
Attendance								
Midterm Exam	0.3810	<.0001	0.3737	<.0001	0.4143	<.0001	0.3737	<.0001
Algebra Compass Entrance Exam					~~**-0.3504**~~	~~**0.3384**~~		
Pre-Algebra Compass Placement	0.2921	0.0049	0.2590	0.0093	0.3105	0.0159	0.2590	0.0093
Freshman (Freshman=1, Sophmore=0)								
Female (Female =1, Male =0)	10.8660	0.0087	10.4771	0.0079	11.9131	0.0048	10.4771	0.0079
Black					~~**-6.0800**~~	~~**0.1197**~~		
Hispanic								
Asian								
NHWhite (Non-Hispanic White)								
LSES (Low Socioeconomic Status)								
SeasonF (Fall = 1, Spring = 0)								
ClassTimeM (Morning = 1, Afternoon = 0)								

Note. Highlighted columns converge to the same model. Independent variables that are not significant at the 5% level are identified by beta and correponding p-values in bold.

In order to modify the best SBC model into a model with only significant predictors, the investigator employed the backward elimination. The result was depicted in Table 4.24 under the SBC + Backward column. The multiple linear regresssion model started with the six predictors from the minimized SBC model and systematically removed the insignificant variables one step at a time with p-values greater than 0.05. The beta and corresponding p-values were recalculated for each step of the backward elimination. Table 4.25 displays this modified SBC with backward elimination as well as summary of the insignificant variables removed during the elimination process.

Table 4.24 shows that when the investigator used the heuristic backward, forward and stepwise eliminations to identify the best model, all converged to the same subset of predictors as the SBC with backward elimination model. The heuristic models (n = 50) account for 57%, r-squared = 0.571, of the variance in the CBT Final examination; however, the SBC with backward elimination model (n = 55) accounts for 56%, r-squared = 0.555 . With closer examination, when the same number of observations (n = 55) are used then the heuristic models and SBC with backward elimination model have identical beta and p-values as seen in the Max Obs Heuristic and Max Obs SBC + Backward columns in Table 4.24.

To elaborate on the model for hybrid sections it is expressed in equation form:

$$CBT\ Final\ Exam = 0.1751 * Quiz + 0.3737 * Midterm\ Exam + 0.2590 * PreAlg.Compass + 10.4771 * Female + 17.6743.$$

Table 4.25

Multiple Linear Regression model by SBC after Backward Elimination: Hybrid Sections

Summary of Backward Elimination							
Step	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Algebra Compass Entrance Exam	5	0.0084	0.5704	5.9355	0.94	0.3384
2	Black	4	0.0162	0.5542	5.7400	1.81	0.1852

Heuristic Backward CBT Best Model w/ Demo by SBC w/ Midterm by Type: Hybrid

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	71
Number of Observations Used	54
Number of Observations with Missing Values	17

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	9695.34301	2423.83575	15.23	<.0001
Error	49	7797.99032	159.14266		
Corrected Total	53	17493			

Root MSE	12.61518	R-Square	0.5542
Dependent Mean	73.77778	Adj R-Sq	0.5178
Coeff Var	17.09888		

Parameter Estimates							
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Type II SS	Standardized Estimate
Intercept	1	17.72161	7.49444	2.36	0.0221	889.84579	0
Midterm Exam	1	0.37121	0.08753	4.24	<.0001	2862.18813	0.43597
Quiz	1	0.17772	0.05615	3.16	0.0027	1594.11923	0.31534
Female	1	10.41281	3.82971	2.72	0.0090	1176.50041	0.27272
Pre-Algebra Compass Placement	1	0.25803	0.09671	2.67	0.0103	1132.93580	0.28272

The Female variable is the only significant demographic predictor. According to this model, women , who account for an estimated 67% of the hybrid sections' population , score approximately 10.4771 points higher than their male counterparts. According to the model, the only impactful OPREP assignment was the Quiz. A 1 point increase in Quiz average yields a 0.32 point increase in the CBT Final examination score. The most impactful non-OPREP assignment was the Midterm Exam. A 1 point increase in Midterm examination score yields approxiamtely a 0.17 point increase in the CBT Final examination score. It is important to note that each additional point on the Algebra Compass placement examination results in a 0.58 point increase in the CBT Final examination score.

Table 4.26 provides a snapshot of the predictions made by the hybrid model. Of the 71 observations, 16 observations were not used because of missing values. Of the 55 remaining observations, the model correctly predicted the passing status of 82% (46/55) of the students who took the CBT Final examination. The remaining 18% respresents the 10 incorrectly predicted students' passing status. Six of the 10 incorrect projections predicted that students would pass when they failed (see observations 71 in Table 42). Examples of the remaining four students who were projected to fail but passed, can be seen in observations 20 and 50 in Table 4.26. In aggregate 44 students (approximately 80%) passed the CBT Final examination. The model slightly overpredicted the number of students passing by projecting 46 (approximately 84%).

Table 4.26

Snapshot of Model Predictions: Hybrid Sections (n =71)

$\boldsymbol{Model}$: $CBT\ Final\ Exam = 0.1751 * Quiz + 0.3737 * Midterm\ Exam + 0.2590 * PreAlg.Compass + 10.4771 * Female + 17.6743$

Output Statistics

Obs	Actual Value (Dependent Variable)	Predicted Value	Std Error Mean Predict	Residual	Std Error Residual	Student Residual	Cook's D	Actual Status	Predicted Status
1	96	98.647	3.9326	-2.647	11.862	-0.223	0.001	Pass	Pass
5	76	76.445	2.6883	-0.445	12.204	-0.036	0	Pass	Pass
6	88	75.1668	5.0504	12.8332	11.431	1.123	0.049	Pass	Pass
7	80	77.5048	2.1464	2.4952	12.311	0.203	0	Pass	Pass
8	84	87.4095	3.8464	-3.4095	11.89	-0.287	0.002	Pass	Pass
9	84	79.3115	3.2167	4.6885	12.076	0.388	0.002	Pass	Pass
10	56	54.7832	5.1723	1.2168	11.376	0.107	0	Fail	Fail
15	80	73.1743	3.5725	6.8257	11.975	0.57	0.006	Pass	Pass
16	88	90.8184	4.7372	-2.8184	11.564	-0.244	0.002	Pass	Pass
17	88	78.8233	5.2846	9.1767	11.324	0.81	0.029	Pass	Pass
20	60	59.5436	3.2119	0.4564	12.077	0.038	0	Pass	Fail
33	68	74.0053	2.4472	-6.0053	12.255	-0.49	0.002	Pass	Pass
34	72	88.0329	2.6201	-16.0329	12.219	-1.312	0.016	Pass	Pass
35	52	53.2432	3.9873	-1.2432	11.844	-0.105	0	Fail	Fail
36	76	63.5105	3.7852	12.4895	11.91	1.049	0.022	Pass	Pass
37	80	86.1328	2.501	-6.1328	12.244	-0.501	0.002	Pass	Pass
50	92	58.7913	3.677	33.2087	11.944	2.78	0.147	Pass	Fail
51	84	88.3911	5.2584	-4.3911	11.337	-0.387	0.006	Pass	Pass
52	80	76.8734	3.2645	3.1266	12.063	0.259	0.001	Pass	Pass
57	80	83.2056	2.2977	-3.2056	12.284	-0.261	0	Pass	Pass
58	100	99.5541	4.2707	0.4459	11.744	0.038	0	Pass	Pass
59	24	39.3253	5.201	-15.3253	11.363	-1.349	0.076	Fail	Fail
60	64	69.9428	4.2479	-5.9428	11.753	-0.506	0.007	Pass	Pass
61	88	88.5387	2.7192	-0.5387	12.197	-0.044	0	Pass	Pass
62	92	96.3554	3.6995	-4.3554	11.937	-0.365	0.003	Pass	Pass
63	92	87.9101	3.066	4.0899	12.115	0.338	0.001	Pass	Pass
70	88	63.862	4.1063	24.138	11.803	2.045	0.101	Pass	Pass
71	56	67.4066	4.3058	-11.4066	11.732	-0.972	0.025	Fail	Pass

Sum of Residuals	0
Sum of Squared Residuals	7808.482
Predicted Residual SS (PRESS)	9608.947

Multiple Linear Regression Model: ASAP Sections

The SBC column of Table 4.27 depicts the best model based on minimizing SBC for the ASAP class-type. The model that minimized SBC included the following predictors: Midterm Practice, Aggregated log-in days and Midterm Exam. Only two of the three predictors are significant at the 5% level. The Midterm Exam variable has a p-value of 0.1391.

Table 4.27

Best Multiple Linear Regression model by SBC Information Criteria Measure: ASAP

	Dependent Variable: 'CBT Final Exam'n							
	ASAP Sections							
	Heuristic				Information Criteria			
Model Selection Measures:	Stepwise	p-value	Max Obs Heuristic	p-value	SBC	p-value	SBC + Backward	p-value
Schwartz Baysian Criterion (SBC):	248.577		278.990		280.593		278.990	
Baysian Information Criterion (BIC):	246.487		275.369		275.264		275.369	
Akaike Information Criterion (AIC):	242.963		273.023		272.637		273.023	
Root Mean Square Error (RMSE):	12.190		12.195		12.047		12.195	
Mallows CP (CP):	-4.506		3.000		4.000		3.000	
R-squared (R^2):	0.301		**0.325**		0.354		**0.325**	
Number of Observation Read:	54		54		54		54	
Number of Observation Used:	48		54	Max Obs	54	Max Obs	54	Max Obs
Independent Variables / Predictors								
Intercept	51.1598	<.0001	48.7393	<.0001	38.9678	0.0001	48.7393	<.0001
In Class Assigments Average								
Homework Average								
Quiz								
Midterm Practice	0.1938	0.0014	0.2094	0.0003	0.1678	0.0073	0.2094	0.0003
Aggregated time spent								
Aggregated activities								
Aggregated log-in days	0.4005	0.0287	0.4503	0.0106	0.4308	0.0135	0.4503	0.0106
Attendance								
Midterm Exam					**0.1635**	**0.1391**		
Algebra Compass Entrance Exam								
Pre-Algebra Compass Placement								
Freshman (Freshman=1, Sophmore=0)								
Female (Female =1, Male =0)								
Black								
Hispanic								
Asian								
NHWhite (Non-Hispanic White)								
LSES (Low Socioeconomic Status)								
SeasonF (Fall = 1, Spring = 0)								

Note. Highlighted columns converge to the same model. Independent variables that are not significant at the 5% level are identified by beta and correponding p-values in bold.

To modify the best SBC model into a model with only significant predictors, the investigator employed backward elimination. The result is depicted in Table 4.27 under the SBC + Backward column. The multiple linear regresssion model started with the three predictors from the minimized SBC model and systematically removed the insignificant variables one step at a time with p-values greater than 0.05. The beta and corresponding p-values were recalculated for each step of the backward elimination. Table 4.28 displays this modified SBC with backward elimination as well as summary of the insignificant variable removed during the elimination process.

Table 4.28

Multiple Linear Regression model by SBC after Backward Elimination: ASAP Sections

Summary of Backward Elimination

Step	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Midterm Exam	2	0.0292	0.3247	4.2593	2.26	0.1391

Heuristic Backward CBT Best Model w/ Demo by SBC w/ Midterm by Type: ASAP

The REG Procedure
Model: MODEL1
Dependent Variable: CBT Final Exam

Number of Observations Read	54
Number of Observations Used	54

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	3647.52363	1823.76181	12.26	<.0001
Error	51	7584.47637	148.71522		
Corrected Total	53	11232			

Root MSE	12.19489	R-Square	0.3247
Dependent Mean	78.66667	Adj R-Sq	0.2983
Coeff Var	15.50197		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Type II SS	Standardized Estimate
Intercept	1	48.73931	6.88653	7.08	<.0001	7449.26291	0
Midterm Practice	1	0.20943	0.05383	3.89	0.0003	2251.06777	0.45001
Aggregated log-in days	1	0.45028	0.16975	2.65	0.0106	1046.47239	0.30683

Table 4.27 shows that when the investigator used the heuristic backward, forward and stepwise eliminations to identify the best model, all converge to the same subset of predictors as the SBC with backward elimination model. The heuristic models (n = 48) account for 30%, r-squared = 0.301, of the variance in the CBT Final examination; however, the SBC with backward elimination model (n = 55) accounts for 32%, r-squared = 0.3247 . With closer examination, when the same number of observations (n = 55) are used then the heuristic models and SBC with backward elimination model have identical beta and p-values as seen in the Max Obs Heuristic and Max Obs SBC + Backward columns in Table 4.27.

To elaborate on the model for ASAP sections it is expressed in equation form:

$$CBT\ Final\ Exam$$
$$= 0.2094 * \text{Midterm Practice} + 0.4503 * \text{Aggregated login days} + 48.7393\,.$$

The are no significant demographic predictors. According to the model, the only impactful OPREP assignment was the Midterm Practice examination. A 1 point increase in Midterm Practice examination average yields a 0.21 point increase in the CBT Final examination score. There are no impactful non-OPREP assignments. The ASAP sections' model is the only model with a significant OPREP metric for time and activity. A 1-day increase in Aggregated log-in days yields approxiamtely a 0.45 point increase in the CBT Final examination score.

Table 4.29 provides a snapshot of the predictions made by the model. All 54 observations, were used. The model correctly predicted the passing status of 94% (51/54) the students who took the CBT Final examination. The remaining 6% respresents the 3 incorrectly predicted students' passing status. All 3 incorrect projections predicted that students would pass when they failed (see observations 19 and 53 in Table 4.29). In aggregate 50 students (approximately 91%) passed the CBT Final examination. The model slightly overpredicted the number of students passing by projecting 53 (approximately 96%).

Table 4.29

Snapshot of Model Predictions: ASAP Sections (n =54)

$\boldsymbol{Model}$: $CBT\ Final\ Exam = 0.2094 * Midterm\ Practice + 0.4503 * Aggregated\ login\ days + 48.7393$

Output Statistics

Obs	Actual Value (Dependent Variable)	Predicted Value	Std Error Mean Predict	Residual	Std Error Residual	Student Residual	Cook's D	Actual Status	Predicted Status
1	76	88.2994	2.6103	-12.2994	11.912	-1.033	0.017	Pass	Pass
2	92	83.9432	2.3959	8.0568	11.957	0.674	0.006	Pass	Pass
6	84	86.3457	2.3159	-2.3457	11.973	-0.196	0	Pass	Pass
7	84	78.2043	1.9892	5.7957	12.032	0.482	0.002	Pass	Pass
8	92	84.7854	2.2366	7.2146	11.988	0.602	0.004	Pass	Pass
9	72	71.8936	2.2211	0.1064	11.991	0.009	0	Pass	Pass
10	68	73.1485	2.9898	-5.1485	11.823	-0.435	0.004	Pass	Pass
14	92	92.4986	3.5231	-0.4986	11.675	-0.043	0	Pass	Pass
15	96	86.1931	2.4085	9.8069	11.955	0.82	0.009	Pass	Pass
16	88	83.2178	2.7414	4.7822	11.883	0.402	0.003	Pass	Pass
19	56	64.1566	3.379	-8.1566	11.717	-0.696	0.013	Fail	Pass
20	96	87.1012	2.4303	8.8988	11.95	0.745	0.008	Pass	Pass
21	56	57.7405	4.5835	-1.7405	11.301	-0.154	0.001	Fail	Fail
26	80	84.0255	2.0035	-4.0255	12.029	-0.335	0.001	Pass	Pass
27	96	88.5956	2.603	7.4044	11.914	0.621	0.006	Pass	Pass
28	92	96.801	5.7549	-4.801	10.752	-0.447	0.019	Pass	Pass
29	60	60.7698	3.9768	-0.7698	11.528	-0.067	0	Pass	Pass
40	84	82.3678	1.9981	1.6322	12.03	0.136	0	Pass	Pass
41	60	75.6136	2.2116	-15.6136	11.993	-1.302	0.019	Pass	Pass
45	80	79.5189	2.1014	0.4811	12.012	0.04	0	Pass	Pass
46	80	76.3429	2.8759	3.6571	11.851	0.309	0.002	Pass	Pass
47	72	61.3443	4.0549	10.6557	11.501	0.927	0.036	Pass	Pass
48	76	76.0908	2.2336	-0.0908	11.989	-0.008	0	Pass	Pass
49	92	78.886	2.8171	13.114	11.865	1.105	0.023	Pass	Pass
50	72	77.865	1.7751	-5.865	12.065	-0.486	0.002	Pass	Pass
51	72	73.1116	4.2269	-1.1116	11.439	-0.097	0	Pass	Pass
52	64	77.7746	3.0303	-13.7746	11.812	-1.166	0.03	Pass	Pass
53	56	71.8116	2.2346	-15.8116	11.988	-1.319	0.02	Fail	Pass
54	64	75.0967	1.8099	-11.0967	12.06	-0.92	0.006	Pass	Pass

Sum of Residuals	0
Sum of Squared Residuals	7584.476
Predicted Residual SS (PRESS)	8634.956

CHAPTER V
DISCUSSION

Incorporate Student Experiences into Implementation Strategies

Importance of the OPREP gradebook. The central phenomenon revealed in the results of the first two research questions was the student need for detailed and relevant feedback when using an online preparation and rigorous enhancement platform (OPREP) such as WebAssign. On a macro level, this feedback was manifested in the students' ability to immediately view their overall grades at any instance during the semester. Of all the features included in the student experience questionnaire, viewing one's grades was the most frequently used. Several students discussed the importance of being able to track their grade and how this progress report functioned as a motivating factor. According to Elliott and Dweck (1988), performance goals (often extrinsic) or learning goals (often intrinsic) are generally exhibited by students on the path to achievement. In this context, a good grade or a passing grade can be considered a performance goal. Some students are motivated to earn good grades while others are motivated to avoid failing; these are just two options on the spectrum of achievement goals that possibly affect a student's learning outcome (Dowson & McInterney, 2004). The ramifications of failing (time, finances, emotional toil and opportunities) and having to repeat elementary algebra, a prerequisite course, can be considered external motivators for all students.

Simon credited motive and emotion as prominent influences on cognitive behavior (Simon, 1967). Avoidance of the possible detrimental repercussions of failing provides adult students with the tangible need to learn that Knowles referred to. Adult students "experience a need to learn in order to cope more satisfyingly with real-life tasks or problems" (Knowles, 1980, p 44). Viewing a perceived low grade can facilitate self-directed learning by motivating students to change (or seek help to change) their study habits in order to improve their performance thus increasing their grade. Tracking grades can impact an adult learner's motivation to learn. A student's response to viewing their overall grade or an assignment grade can be a reflection of an internal priority such as self-esteem. Fidishun (2000) stated, "Activities that build students' self-esteem, or sense of accomplishment through, for example, the completion of goals or modules that can be checked off in a sequence, may help motivate completion of a longer lesson" (p. 4). Seeing that their effort lead to a correct answer, a completed assignment or increase in overall grade can result in a sense of accomplishment and possibly positively impact on student self-esteem.

Administrators and faculty can use students' views (e.g., importance of viewing grades) as a firm basis to make better decisions when adopting and implementing online educational technology. For example, on WebAssign students can see their grades on individual assignments but cannot track their overall grades unless an instructor sets up a gradebook. Departments requiring the implementation of an OPREP should make an appropriate gradebook mandatory. The word "appropriate" is used because some OPREPs have default gradebooks that give students a false impression of their progress because the gradebook does not automatically include missing assignments in the student's overall grade calculations. That means if a student averages a 90% on the first three assignments but does not attempt the remaining 10 assignments, the students overall grade will still appear as 90%, thereby misleading uninformed instructors and students would have a false impression.

Another recommendation involving the gradebook relates to an assignment due date. Some instructors leave all assignments open until the end of the semester. This policy neglects the value of setting deadlines and benchmarks for students. Specifically, students are unaware of their progress because the gradebook does not (or should not) include an assignment in a student's overall grade until after the assignment deadline. If the due date is the last week of the semester, then the student loses the chance for macro-level immediate feedback in terms of constant progress reports in the form of her/his overall grades. The gradebook is defined as a feature, but is similar to a learning tool; it promotes student learning through tapping into extrinsic motivation associated with passing or the fear of failure and its ramifications. If there is a desire to give students more time and opportunity to complete assignments, then this can be accomplished with appropriate due dates and enabling automatic extensions with adequate penalties. Departmental administrators could require faculty members to set appropriate due dates, thus providing appropriate benchmarks and immediate feedback in term of student's overall grades. The student's desire to have immediate feedback (constant progress reports) is undeniable and should not be ignored, especially when it can be reasonably accommodated.

This recommendation includes adding offline assignments such as paper-based quizzes, midterm examinations, and projects into the gradebook. It can be accomplished by creating a placeholder assignment with the name of the assignment (e.g., Midterm) that can be distributed to faculty at the beginning of the semester. Student scores can be inputted directly into the OPREP or uploaded from a spreadsheet. The students in this study were able to view their grades for each assignment category: attendance, in-class, homework, quiz, midterm, practice midterm, cumulative quiz, practice final, departmental final examination and CBT final examination. They were able to view that category's impact on their projected overall grade at any time during the semester. Their OPREP gradebook included scores for a paper-based midterm, departmental final examination and CBT final examination as well as a placeholder assignment to track attendance.

Importance of the OPREP extensions. Viewing a perceived low grade can facilitate self-directed learning by motivating students to change (or seek help to change) their study habits in order to improve their performance thus increasing their grade. Several studies, including Hirsch (2003), have mentioned the problem of students not completing their web-based homework assignments. The gradebook informs the instructor, and the student, of current progress through the OPREP assignments and makes any patterns in student effort (or lack of effort) apparent to both parties before a summative assessment. Through requesting assignment extensions, students in this study had the opportunity to improve their grades by revisiting assignments. OPREPs with extension abilities require an OPREP instructor or departmental OPREP coordinator to define an extension policy. In this study, the instructor set up an automatic extension option to minimize students explaining the need for an extension and reduce the time required for an instructor to grant a manual extension. (Automatic extensions were not available for high stakes assessments such as an in-class quiz or examination.) The results show that the students found the extensions option invaluable.

Though extensions were the second least used OPREP feature, students mentioned their importance as a stress reliever and a vehicle to improve their grades. The combination of the ability to view current grades and request assignment extensions resulted in a self-regulatory response. Self-regulation is the generation of actions, feelings and thoughts in pursuit of a particular goal through reflection (Schunk & Zimmermann, 1994). During the semester, students reflected on their current grades, and, ideally, set a goal to increase those grades. This reflection resulted in the act of requesting an extension. The existence of extensions facilitated the students' beliefs that they could change the trajectory of their semester. Student self-efficacy within this context influenced self-regulation. "The perceived usefulness of a Web-based tool is an outcome expectation, a facet of self-efficacy influencing self-regulation" (Liaw, 2002, as cited in Hauk, 2005, p239). Hauk's work focused on the persistence a student displays within an OPREP homework assignment (e.g., when reworking the assignment based on feedback about its correctness); however, it can be extended to OPREP features (i.e., gradebook and extensions), which exist outside assignments.

In the current study reported here, it is important to recognize that no students were required to use these learning tools or features (except notifications) but they voluntarily choose to use them to enhance their learning experiences. The students were exposed to features and instructed on how to use them at the beginning of the semester.

> It is also important that self-directedness not be confused with self-motivation. Although a student may be motivated to take a course; they may not be self-directed enough to feel comfortable … creating their own structured environment to learn in a web-based course. Encouraging self-directedness may also take the form of additional instructor contact in the beginning stages of the class. (Fidishun, 2000, p. 2)

Exposing the students to these features and learning tools in the first meetings set the precedence of their importance and it was unnecessary to emphasize their use throughout the semester. Once exposed, students saw their value and used the appropriate features accordingly. Even the students who preferred paper-based assignments did not deny the value of WebAssign's immediate feedback.

OPREP learning tools as feedback. The central phenomenon of the student need for detailed and relevant feedback when using an OPREP was apparent in the results of the second research question as well. On a micro level, the results show that students use WebAssign's learning tools to receive one-on-one individualized instruction/ feedback within an assignment.

An axiom of web-based homework is that achievement necessitates practice, homework is a vehicle for practice, and improving the speed of feedback will increase student learning (Pascarella, 2004). The level of feedback available to students in this study was scarcely referred to in the literature. Several studies, including Hauk (2015) and Hirsch (2003), reported concerns that the web-based homework system provided immediate feedback only in terms of correctness. Zerr (2007) discussed incorporating detailed feedback in the form of a solution key. He emphasized the importance of the attempt-feedback-reattempt sequence that occurs when students interact with instructors in a classroom and the potential for an OPREP to replicate this sequence through expanded feedback. This study's results support Zerr's premise. The learning tools on WebAssign seem to address Bloom's two-sigma problem; i.e. improving performance more than is achieved in typical, group-based classrooms instruction. Students in the traditional learning condition in this study, through the OPREP, have access to one-on-one individualized instruction when needed, especially outside the classroom.

The majority of students found the learning tools useful and leveraged them to facilitate growth. "In particular, students' perceptions about the usefulness of a Web-based tool, their intentions to use it, and their beliefs about a subject are key determinants of motivation to persist in efforts, in this case to do mathematics, in a Web-based environment" (Liaw, 2002, as cited in Hauk, 2005, p239). In general, the students find this immediate feedback not just useful but essential to their learning process. Students distinctly preferred using affordances such as WebAssign's Practice It (step-by-step interactive tutorial), and the Practice Another Version tool as well as Watch It (lecture videos) more than using the other learning tools. The students' preferences were distinct, but not overwhelming. For example, the scaffolding in Master It (mastery tutorials) was frequently used; however, Read It (electronic textbook) was for the most part only occasionally used.

Previous studies about web-based homework systems mentioned students not utilizing the textbook before starting an assignment. According to Khanlarian, teachers report that due to unlimited attempts to get the right answer, students do not read the chapter first (Khanlarian, 2010). Educators must consider that adult learners desire to know the reason they "need to learn something or how it will benefit them" (Fidishun, 2000, p. 3). If the goal is to complete a homework assignment, then an adult learner may use their current knowledge to attempt to answer a question before recognizing the need to access a learning tool such as the textbook. Forcing students to read the textbook or attempting to control how and when adult learners use these learning tools during a homework assignment is counterproductive because it contradicts an adult learner's self-concept. Knowles, Holton, and Swanson (1998) reported that "adults resent and resist situations in which they feel others are imposing their wills on them" (p. 65). When the students needed help to start a problem or access a higher level of feedback to work through the problem, the e-book was the least used option.

> It becomes extremely important for those who are designing technology-based adult learning to use all of the capabilities of the technology including branching, the ability to skip sections a student already understands, and multiple forms of presentation of material which can assist people with various learning styles. (Fidishun, 2000, p. 4)

Several students referred to the learning tools, which present the material in multiple forms, as a substitute for their professor outside the classroom and expressed the desire to use it in future mathematics courses.

Synergy between OPREP learning tools and the instructor. Although the majority of students appreciated the feedback from the learning tools, no student suggested that such feedback could function as replacement for their instructor. Students generally viewed the learning tools, whether used during an in-class assignment or homework, as supplemental instruction. They were useful as a tool for feedback and essential as a vehicle to enhance their learning, especially outside the classroom. When asked to compare how much they learned in a mathematics course using WebAssign versus one with traditional paper-based assignments, most of the students felt they learned more with WebAssign. Approximately a quarter of the students mentioned the importance of their teacher/ professor. Carl Rogers, American psychologist and developer of facilitation theory, believed that learning relied on human relationships and it could only occur in a nurturing environment for the student (Rogers, 1951). His humanist approach to learning led historically to more recent strategies of student-centered learning. Some students in this study solely credited their professor and how much he cared with their success. One student mentioned liking WebAssign but preferred the in-class experience. A majority of those that mentioned their instructor credited a combination of WebAssign (especially the learning tools) and their instructor for contributing to their growth in knowledge as well as success in the class.

When referencing the importance of the teacher-student relationship, Khanlarian (2010) suggests that communication is the key factor. Khanlarian (2010) states, “If this [facilitation theory] is true then perhaps technology allows people to connect on a level that formerly was reserved for face-to-face communication. Perhaps the important part of face-to-face communication is the communication and not the face-to-face” (p. 67). Students can generally contact their instructor and ask for guidance through an OPREP; however, this form of communication (outside a classroom) does not often result in instantaneous feedback. The immediate feedback from an OPREP in terms of correctness can prompt students to engage in self-regulating activities by seeking help through the learning tools and/or their instructor.

The act of attempting an assignment question and submitting a potential answer initiates a process through which one can diagnosis one's mastery of a learning outcome. If a student struggles (incorrect answer or too many submissions), then it is possible to choose a learning tool (or set of learning tools) to illuminate errors in thinking or to practice the skills she/he has acquired. Through an OPREP, instructors can also provide more resources such as additional lecture videos, PowerPoint lectures and hand written solution keys with commentary. When deemed necessary, an instructor can create a discussion forum to facilitate communication between the instructor and the class. Students seeking to gain proficiency in a learning outcome choose the resource(s) / learning tool(s) that best facilitate the achievement of that goal based on their learning styles. For example, a student factoring a trinomial (where the leading coefficient is an integer greater than one) may click Watch It to access a lecture video on the AC method for factoring trinomials. Then that same student can click Practice It to access an interactive step-by-step tutorial where the system rigorously reviews skills (e.g., greatest common factor and factoring by grouping) required to solve the problem. This student engages in self-directed learning.

> In its broadest meaning, 'self-directed learning' describes a process by which individuals take the initiative, with or without the assistance of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes. (Knowles, 1975, p. 18)

When asked if WebAssign worked well with their learning style, the majority of students referred to their favorite learning tools (e.g., visual learners and video lectures) but they also mentioned the system's overall ability to make their life easier. Some thought the system was easy to use in terms of online access and convenience. Others credited the system with helping them stay focused and organized because their learning path was streamlined and they were able to access most of their resources in one place. According to the students, these qualities facilitated their learning; therefore, the OPREP functioned as an online version of the nurturing environment that Rogers (1951) referred to. Though only 5% of those surveyed reported that WebAssign did not work well with their learning styles it is important to note why. The only student who elaborated on a reason referred to low computer self-efficacy. According to Santhanam, Sasidharan and Webster (2008), computer self-efficacy along with positive feedback and learning orientation influence learning outcomes. Low computer self-efficacy can act as a barrier for students engaging in self-regulatory learning and self-directed learning.

While crediting increased learning to the combination of their professor and working on WebAssign, students also provided enlightening comments. They mentioned knowing their instructor cared about their success. Students valued clear and precise explanations during the lecture. When the learning tools did not facilitate a student's achieving or learning goal, that student self-regulated by seeking additional help from the instructor (both inside and outside of the classroom). Some of the most salient points came from students who repeated elementary algebra in the same college under different instructors. Several multiple repeaters referred to role of the professor's implementation strategy. Santhanam et al. (2008) suggested that instructional strategy is one of the key co-dependent factors (e.g., information technology and the learners' psychological processes) that increase learning outcomes. One multiple repeater stated that she used WebAssign in a class with two successive educators and noted that proper instruction on using an OPREP is essential. Another student spoke about the increased level of immediate feedback she received from WebAssign compared to her previous experience of using WebAssign with a different elementary algebra instructor. This is an important perspective that can mostly be offered by a multiple repeater because elementary algebra is the first course in this college where the students are exposed to WebAssign. When using an OPREP, an appropriate implementation strategy is essential to student achievement. Future research can explore the difference in student experience and student performance based on instructors incorporating different implementation strategies.

Incorporate Student Performance into Implementation Strategies

OPREP assignments related to student achievement. Student achievement, measured by CBT final examination, is significantly ($\alpha = .05$) correlated with several outcomes; i.e. every OPREP assignment, OPREP time and activity metric, and non-OPREP assessment, that were included in this study (see Table 4.17 for a list variables). All correlations were positive, meaning that increase in student performance on any of these variables should coincide with an increase in CBT final examination score. The strength of the correlations varied. Only statistically significant correlation coefficients greater than 0.3 in absolute value are displayed in Table 4.17. Aggregated time spent, Aggregated activities, Aggregated log-in days, and Number of log-ins had relatively weak correlations with the CBT final examination. The Pearson correlation coefficient for Attendance was the only OPREP time and activity measure reported in Table 4.17 but it accounts for just under 10% of the variance in the CBT final examination. Attendance had the strongest relationship with student achievement of all OPREP time and activity measures but the strength of the relationship is weak when compared to any OPREP assignment.

The OPREP Quiz, Practice Final Exam and Practice CBT Final correlations to student achievement were distinctly stronger than the OPREP Homework or In-Class Assignment. This was not surprising because the OPREP assessments are designed to function like traditional paper-based summative assessments. An OPREP Homework or In-Class Assignment is designed to facilitate learning through practice and multiple levels of immediate feedback. The practice examinations, when used correctly, are designed to prepare students for the depth and breadth of a test. OPREP quizzes had a stronger relationship with the CBT final examination than any other OPREP assignment. The correlation coefficient of the quizzes was higher than that of the paper-based departmental midterm examination and both Compass placement examinations (algebra and pre-algebra). The only variable that had a stronger relationship with the CBT final examination was the paper-based departmental final examination. Neither the departmental final examination nor the practice finals can serve as early predictors for student achievement because they are administered within three weeks of the CBT final examination.

Regression analysis was used to determine the most relevant possible independent variables (students' grades on OPREP assignments) and the ability of the variable to predict the dependent variables (student achievement). In terms of a single assignment (or set of assignments), student OPREP quiz average is the strongest early predictor for student achievement. This was supported by the t-test results because the difference in the quiz average of students who passed the exit examination was significantly higher than those who failed. The significant difference was consistent regardless if all class types are considered or individual class types are considered. The effect size of was large, by Cohen's standard, in the ASAP sections, traditional sections and when all sections were considered, but it was medium in the hybrid sections.

An illustration applying the results of the quiz regression model. For illustration purposes, imagine that an instructor wants an early indicator for students who need intervention. This instructor decides to use a student's quiz average to predict student achievment. Considering that the student needs a 60 (15 out of 25) or higher to pass the CBT Final examination, the instructor may choose to use a higher score of 72 (18 out of 25) as a buffer when projecting student success on the final examination. According to the model in Figure 13, the cut-off Quiz average for a student is approximately 61. This student would need to average at least a 61 on the OPREP quizzes to achieve a projected 72 on the CBT Final examination.

It is important to note that this model has limitations. One limitation is the model includes only one predictor and the multiple linear regression results from research question (4) show that better models exist that take into consideration demogrpahic differences. Quiz average as a sole predictor only accounts for 29% of the variance in the CBT Final examination while the multiple linear regression model account for 45% to 60% of the variance. A benefit of using this single predictor model is the instructor saves time by avoiding the possible tedious process of obtaining demographic data and other relevant data. Another limitation is that the model can over predict based on the value of the y-intercept, b = 51.7. This is close to 60, the score needed to pass the CBT Final examination. One suggestion to compensate for this over prediction is to increase the minimum required value (e.g., from 60 to 72 as discussed above) when using the model to detemine a cut-off score. Instructors should consider making a corrective adjustment that slightly reduces a student's projected performance before sharing that value with the student.

There exists a limitation in applicability because the data included three different class types. Welch's ANOVA confirmed that the mean CBT Final examination scores of the three groups (i.e, traditional, hybrid and ASAP) are not the same. This suggest that class type specific models may be more appropriate. The OPREP quiz may, or may not, be the OPREP assignment with the strongest correlation within the class types. Future research can determine the best single predictor model for each class type.

The best multiple regression model for predicting student achievement. The best model included the following predictors: Quiz , Midterm Practice examination, Midterm Exam, Pre-Algebra Compass Placement examination, Hispanic (Hispanic = 1, non-Hispanic = 0) , SeasonF (Fall = 1, Spring = 0). This model accounted for 45% of the variance in the CBT Final examination. In equation form the model may be expressed as:

$$\begin{aligned} CBT\ Final\ Exam &= 0.1939 * \text{Quiz} + 0.0731 * \text{Midterm Practice} + 0.2486 * \text{Midterm Exam} \\ &+ 0.219 * \text{PreAlg. Compass} + 5.2856 * \text{Hispanic} - 7.1805 * \text{SeasonF} + 32.1378. \end{aligned}$$

When every other variable in this model is held constant, Hispanic students outperform their non-Hispanic peers by 5 points. Hispanic students represent 43% of the population in this sample and 38% of the population in the college. According to this model, students enrolled the spring semester outperform their counterparts in the fall semester by 12 points, when all other predictors are kept constant.

An illustration applying the results of the multiple regression model. For illustration purposes, imagine that an instructor wants an early indicator for students who need intervention. This instructor decides to use the most impactful OPREP assignment, a student's quiz average. Considering that the student needs a 60 (15 out of 25) or higher to pass the CBT Final examination, the instructor uses a score of 72 (18 out of 25) for projection purposes to provide the students with a buffer on examination day.

Example of application for non-Hispanic students. In order to calculate the critical value for the Quiz average of a non-Hispanic (Hispanic = 0) student during the fall semester (SeasonF = 1), the instructor uses the means from Table 4.3 to represent the performance of an average student. According to the model in Table 4.20, the cut-off Quiz average for a non-Hispanic average student during the Fall semester is approximately 85. This student would need to average at least a 85 on the OPREP quizzes to achieve a projected 72 on the CBT Final examination. A Quiz average less than 85 would indicate the student is at risk of failing the CBT Final examination and could benefit from early intervention.

One drawback of using this model is the availability of the demographic data needed to identify a student's ethnicity and the time it takes to acquire it. When applied to all the data, this model overpredicted the number of students passing by 5% (see Table 4.20) and correctly predicted the passing status of 86% of the students. The CBT Final examination scores cluster near the top of scatter plots. This over prediction can be a problem when one looks at subsets of students such as Hispanic students in the spring semster. If average scores from Table 4.3 are used to represent an average student then the model predicts that this subset of students can preform poorly on the quiz and still marginally pass the CBT Final examination. One possible solution is parsing the data and finding two separate models, one for Hispanic students and another for non-Hispanic students. Another approach is to find average scores for Hispanic students and use those scores to make projects for the Hispanic students, the largest population. Significant differences in class type presented a limitation that led the researcher to consider class-type specific models.

The best multiple regression model for students in traditional sections. The best model for the traditional classes included the following predictors: Quiz , Midterm Exam, Algebra Compass Placement examination, Pre-Algebra Compass Placement examination, Freshman (Freshman= 1, Sophmore= 0), Hispanic , Non-Hispanic White and SeasonF (Fall = 1, Spring = 0). This model accounted for 60% of the variance in the CBT Final examination. In equation form the model becomes:

$$CBT\ Final\ Exam = 0.3214 * \text{Quiz} + 0.1748 * \text{Midterm Exam} + 0.5795 * \text{Alg. Compass} + 0.2576 * \text{PreAlg. Compass} - 8.0989 * \text{Freshman} + 7.4297 * \text{Hispanic} + 15.1111 * \text{NHWhite} - 12.3963 * \text{SeasonF} + 24.4877.$$

When every other variable in this model is held constant, Hispanic students outperform their non-Hispanic peers by 7 points and White students outperform their non-White peers by 15 points. According to this model, students enrolled the spring semester outperform their counterparts in the Fall semester by 12 points when all other predictors are kept constant. Sophmore students outperform freshman by 8 points and a student's initial ability as measured by the Compass plays a role. OPREP quiz average is the only OPREP assignment in the model. According to this model, the cut-off Quiz average for a Hispanic freshman student during the Fall semester is approximately 87. This Quiz cut-off assumes the average midterm examination, algebra Compass placement examination and the pre-algebra Compass placement examination scores for students in the traditional sections (see Appendix B). One limitation of this model is that Non-Hispanic White students perform significant better than their counterparts but they only represent 8% (11 out of 133) of the population. When applied to all the traditional section data, this model overpredicted the number of students passing by 2% (see Table 4.23) and correctly predicted the passing status of 90% of the students. This is 4% higher than the all class types model.

The best multiple regression model for students in hybrid sections. The best model for the hybrid classes included the following predictors: Quiz , Midterm Exam, Pre-Algebra Compass Placement examination and Female (Female =1, Male = 0). This model accounted for 55% of the variance in the CBT Final examination:

$$CBT\ Final\ Exam = 0.1751 * Quiz + 0.3737 * Midterm\ Exam + 0.2590 * PreAlg.Compass + 10.4771 * Female + 17.6743.$$

When every other variable in this model is held constant, Women outperform their Male counterparts by 10 points. Performance on the midterm examination and a student's initial ability as measured by the Compass play a role. Once again, OPREP quiz average is the only OPREP assignment in the model. According to this model , the cut-off Quiz average for an average male student is approximately 88. This Quiz cut-off assumes that average midterm examination score and the pre-algebra Compass placement examination for hybrid students (see Appendix B). When applied to all hybrid section data, this model overpredicted the number of students passing by 4% (see Table 4.26) and correctly predicted the passing status of 82% of the students. This is 4% lower than the all class types model.

The best multiple regression model for students in ASAP sections. The best model for the ASAP classes included the predictors Midterm Practice and Aggregated log-in days. In order to further elaborate on the model it is expressed in equation form:

$$CBT\ Final\ Exam = 0.2094 * Midterm\ Practice + 0.4503 * Aggregated\ login\ days + 48.7393\ .$$

This model accounted for only 32% of the variance in the CBT Final examination, which is much less when compared to the other class types. This may be an indication that other factors impact ASAP students, such as mandatory tutoring, intrusive advisement and additional financial aid may. Future research that includes these factors may reveal more about ASAP students. The students in the ASAP sections had the highest passing rates and highest average CBT Final examination score.

There are no significant demographic variables in this model. The OPREP quiz average is not a significant predictor. The midterm practice examinations variable is the only OPREP assignment in the model. Aggregated login days is the only OPREP time and activity metric to appear in any model. When this model is applied to all ASAP section data, the model overpredicted the number of students passing by 5% (see Table 4.29) and correctly predicted the passing status of 94% of the students. This is 8% higher than the all class types model. According to this model , to achieve a 72 on the CBT exit examination the cut-off midterm practice examinations average is approximately 35. This midterm practice cut-off assumes that average number of aggregated login days for ASAP students, 35 (see Appendix B). If the average midterm practice examination score for ASAP students (i.e., 67) is used, then the cut-off aggregated login days is approximately 21. If the OPREP provides the instructor with the average weekly log-ins then mulitplying by the number of weeks in the term provides a projection of the students aggregated log-in days. This measure can be used as an early indicator for ASAP students needing interention. Future research of the effectiveness of such a measure is suggested.

Conclusion

The central phenomenon was the importance of the immediate relevant feedback on WebAssign to the students' learning process, including their motivation. On a macro level the constant progress report in the form of the student's overall grade and how individual assignments impact that grade was essential. The students valued the ability to track their grades at any time and request extensions when necessary to improve those grades. Combining the gradebook with extensions facilitated self-directed learning and self-regulated learning in an online environment where students could control the trajectory of their performance. On a micro level, the immediate feedback through learning tools inside assignments was essential outside the classroom. These learning tools also facilitated self-regulation by allowing a student to create a successful path to achieving a learning outcome. The nature of the feedback extended beyond correctness. Students preferred to use interactive step-by-step tutorials, practice different versions of the problem, and watch lectures more than any other learning tool.

The instructor's implementation was a point of emphasis for key students. Multiple repeaters of elementary algebra stressed the importance of the OPREP implementation strategy on their achievement. Comments range from differences in the availability and strategic deployment of the learning tools to proper instruction on how a student should use the OPREP. The literature shows that OPREPs are typically employed to replace the tedious and time-consuming grading of paper-based homework. Ignoring the testing management features of an OPREP, and limiting it to using web-based homework tool, is a reflection on the importance of an implementation strategy. Although this study confirms a significant and relative large correlation between homework and an exit examination, it also shows that OPREP assessments, such as quizzes and practice examinations, have stronger positive correlations. Results showed that an OPREP quiz average was the best sole predictor in the linear regression analysis. OPREP quiz average was also the only OPREP assignment variable that was a significant predictor in the multiple linear regression. Mathematics Departments using OPREPs should choose an OPREP with adequate macro and micro level immediate feedback. The recommendations to improve OPREP implementation strategies include setting up an appropriate gradebook, providing access to robust learning tools, using OPREP assessments (e.g., quizzes and practice examinations) and creating a student-centered extension policy.

When class type was considered, OPREP quiz average remained the only predictor out of the OPREP assignments for traditional and hybrid classes. The model for both class types included demographic variables and initial mathematic ability variables. The multiple regression model for the ASAP elementary algebra classes used midterm practice average (OPREP assignment) and Aggregated log-in days (OPREP time and activity metric) as its only predictors. The students in the ASAP sections had highest passing rates and highest average CBT Final examination score. Future research to improve the class type models are recommended. For example, an ASAP multiple linear regression model including outside factors (mandatory tutoring and intrusive advisement) impacting ASAP may account for a higher percentage of the variance for student achievement. Future research that includes these factors may reveal more about ASAP students.

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APPENDIX A

Table A.1

Results of the ANOVA by Group, Levene's test and Welch's ANOVA

Example of one-way ANOVA CBT Final Passing Rate & Groups

The ANOVA Procedure

Levene's Test for Homogeneity of Passing Rate Variance ANOVA of Squared Deviations from Group Means					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Group	7	113972	16281.8	6.24	<.0001
Error	42	109631	2610.3		

Welch's ANOVA for Passing Rate			
Source	DF	F Value	Pr > F
Group	7.0000	137.60	<.0001
Error	15.9153		

Note. The CBT Final examination mean passing rate for researchers' class types was compared to different groups in the university system. Levene's test for homogeneity of variances has a p-value less than .0001, which is less than the critical 0.05 alpha value. This means the null hypothesis of homogenous variances is rejected. Welch's test performs an ANOVA without the homogeneity of variances assumption. According to Welch's ANOVA, the means of the eight groups (listed in Table A.2) are statistically significantly different at the 5% confidence level (p-value <.0001 < 0.05). At least one group has an average passing rate not equal to the others.

Table A.2

SNK test post hoc ANOVA test comparing difference between eight groups

Example of one-way ANOVA CBT Final Passing Rate & Groups

The ANOVA Procedure

Student-Newman-Keuls Test for Passing Rate

Note: This test controls the Type I experimentwise error rate under the complete null hypothesis but not under partial null hypotheses.

Alpha	0.05
Error Degrees of Freedom	42
Error Mean Square	41.45646
Harmonic Mean of Cell Sizes	5.941645

Note: Cell sizes are not equal.

Number of Means	2	3	4	5	6	7	8
Critical Range	7.5384951	9.0754895	9.9925115	10.645666	11.151575	11.563651	11.910569

Means with the same letter are not significantly different.

SNK Grouping		Mean	N	Group
	A	92.013	4	Researcher ASAP Sections
	B	83.062	8	Researcher All Sections
	B			
	B	78.924	5	Researcher Hybrid Sections
	B			
	B	74.913	5	Researcher Traditional Sections
	C	59.143	7	4-years College
	C			
D	C	55.000	7	Entire University System
D	C			
D	C	54.143	7	2-years College
D				
D		47.429	7	Community College

In Table A.2's SNK "grouping" column, groups with the same letter are not significantly different. This means that the average CBT Final examination passing rate of this study's community college (47%), is not signicantly different from the average passing rate of the entire university system (55%) or all 2 year colleges (54%) in the university system. This is because all three groups (community college, 2 year colleges, entire university system) have the letter D under the SNK grouping column. Similarly, the average CBT Final examination passing rate of the researcher's hybrid group (79%) , is not signicantly different from the average passing rate of the researcher's traditional group (75%) or all the researcher's sections (83%). This is because all three groups (researcher's hybrid group, researcher's traditional group and all the researcher's sections) have the letter B under the SNK grouping column. The statistically significant group difference lies between the researcher's groups and the university groups shown by the different letters in the SNK grouping column. The researcher's groups have the letters A or B under the SNK grouping column, while the university (or its subdivisions) have the letters C or D. All the groups in this study have statistically higher average CBT Final examination passing rates than university (or its subdivisions). On average the passing rate of all the researcher's sections (83%) are 28% higher than the entire university system (55%).

APPENDIX B

Table A.3

Tradition Sections: Descriptive statistics of continuous variables: number of observations, arithmetic mean, standard deviation, sum, minimum and maximum

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
CBT Final Exam	136	71.18	19.19	9680	20	100
Final Exam	136	64.78	24.61	8810	0	100
Quiz	136	64.68	31.31	8797	0	111
In Class Assignments Average	136	71.27	26.82	9693	0	100
Homework Average	136	67.95	25.71	9241	3.67647	101
Aggregated time spent	136	2591.00	1292.00	352437	346	7395
Aggregated activities	136	513.51	225.80	69838	46	1334
Aggregated log-in days	136	33.41	9.77	4544	14	64
Number of log-ins	75	39.55	14.26	2966	14	81
Cumulative Quiz	96	56.20	31.66	5395	0	100
Practice Final Exam	79	44.81	33.41	3540	0	100
Practice CBT Final	96	57.01	30.01	5473	0	100
Midterm Practice	136	47.15	35.05	6413	0	100
Midterm Exam	136	70.09	23.65	9533	0	98
Attendance	136	77.82	15.48	10583	33.92857	104
AlgCompassEntrance	124	20.59	5.40	2553	15	37
PreAlgCompassEntrance	125	33.08	16.35	4135	17	84

Table A.4

Hybrid Sections: Descriptive statistics of continuous variables: number of observations, arithmetic mean, standard deviation, sum, minimum and maximum

Simple Statistics						
Variable	**N**	**Mean**	**Std Dev**	**Sum**	**Minimum**	**Maximum**
CBT Final Exam	71	74.59	19.48	5296	20	100
Final Exam	59	70.32	24.91	4149	0	100
Quiz	71	63.30	31.24	4494	0	102
In Class Assignments Average	71	76.08	25.54	5402	15.5215	100
Homework Average	71	74.79	23.06	5310	11.53846	101
Aggregated time spent	71	2265.00	1401.00	160804	175	7065
Aggregated activities	70	411.86	179.65	28830	44	790
Aggregated log-in days	71	25.92	12.07	1840	1	62
Number of log-ins	45	28.09	15.03	1264	1	76
Cumulative Quiz	33	67.95	36.35	2242	0	100
Practice Final Exam	26	43.87	32.38	1141	0	88
Practice CBT Final	57	62.58	33.13	3567	0	100
Midterm Practice	59	61.03	36.69	3601	0	100
Midterm Exam	59	74.79	22.20	4412	0	98
Attendance	71	79.61	18.78	5652	25	100
AlgCompassEntrance	65	22.89	6.91	1488	15	38
PreAlgCompassEntrance	66	42.00	21.05	2772	17	94

Table A.5

ASAP Sections: Descriptive statistics of continuous variables: number of observations, arithmetic mean, standard deviation, sum, minimum and maximum

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
CBT Final Exam	54	78.67	14.56	4248	56	100
Final Exam	54	78.44	20.66	4236	0	100
Quiz	54	74.19	23.90	4006	15.75554	108
In Class Assignments Average	54	77.38	25.12	4179	8.19672	100
Homework Average	54	82.51	19.16	4456	11.79487	100
Aggregated time spent	54	2649.00	1351.00	143031	647	8712
Aggregated activities	54	539.93	179.28	29156	119	947
Aggregated log-in days	54	35.43	9.92	1913	14	68
Number of log-ins	34	43.68	13.29	1485	17	84
Cumulative Quiz	34	65.60	29.72	2230	0	99
Practice Final Exam	20	43.40	31.46	868	3	94
Practice CBT Final	34	62.25	32.96	2116	0	100
Midterm Practice	54	66.73	31.28	3604	0	100
Midterm Exam	54	80.97	17.27	4373	0	100
Attendance	54	84.56	13.78	4566	41.07143	100
AlgCompassEntrance	49	24.00	6.78	1176	15	38
PreAlgCompassEntrance	49	45.39	18.07	2224	18	97

APPENDIX C

Student OPREP/ WebAssign Experience Questionnaire

Q1.

Did your instructor introduce Enhanced WebAssign (EWA) and explain its use at the beginning of your course?

- ◯ Yes, my instructor introduced and explained EWA to the students on the first day of class
- ◯ Yes, my instructor introduced and explained EWA to the students during one of the first class meetings
- ◯ No, my instructor did not introduce or explain how EWA would be used in the course
- ◯ I do not know because I missed a few class meetings

Q2.

Did you work on the "Entering Math Answer into EWA" assignment at the beginning of the course?

Yes	No	Not Applicable
◯	◯	◯

Q3.

Did you use Enhanced WebAssign (EWA) before this course?

Yes	No
◯	◯

Q4.

If you did use EWA before this course, was it the same instructor?

Yes, Same Instructor	No, Different Instructor	N/A, This is my first using EWA
◯	◯	◯

Q5.
In what Mathematics course(s) have you used Enhanced WebAssign (EWA)?

- ☐ MAT 051 (Elementary Algebra)
- ☐ MAT 056 (Intermediate Algebra and Trigonometry)
- ☐ MAT 206 (PreCalculus)
- ☐ MAT 012 (Basic Arithmetic and Algebra)
- ☐ MTH 16 (Finite Mathematics)
- ☐ MAT 121 (Calculus I)
- ☐ MAT 122 (Calculus II)
- ☐ MAT 120 (Pre-Calculus)
- ☐ MTH 30 (PreCalculus)
- ☐ MTH 10 (Intermediate Algebra)

Q6.
The following questions are about your use of the features of Enhanced WebAssign (EWA). How often did you use the following feature?

	Not At All	Occasionally	Frequently
View your Grades on EWA	○	○	○
Used the Personal Study Plan	○	○	○
Request Assignment Extensions in EWA	○	○	○
Read Announcements on EWA /Used links in Announcements	○	○	○
Viewed the Calendar for Assignment due dates and times in EWA	○	○	○
Used Resources that your instructors posted in the Resource section	○	○	○
Received email Notifications about Assignments & other Communications	○	○	○

Q7.
Were the feature(s) of Enhanced WebAssign (Grades, Extensions, Announcements, Calendar, Resources, Notifications, Personal Study Plan, other) useful to you? Why?

Q8.

The following questions are about your use of the learning tools of Enhanced WebAssign (EWA). How often did you use the following learning tools while working on your EWA assignments?

	Not At All	Occasionally	Frequently
"Read It"/ eBook/ YouBook	○	○	○
"Watch It" / Video Lectures	○	○	○
"Practice It"/ Step by Step Interactive Tutorials	○	○	○
"Master It"/ Additional Concept Mastery Tutorials	○	○	○
"Practice Another Version"	○	○	○

Q9.

Were the learning tools ("Read It" , "Watch It", "Practice It", "Master It", "Practice Another Version") in your Enhanced WebAssign assignments useful to you? Why?

Q10.

For this question, please consider how often you have read/used your paperback textbooks in past Mathematics courses. In Enhanced WebAssign, you can use "Read It" to take you to the relevant sections of the eBook/Youbook (electronic version of your textbook). Did you read/use the eBook/ YouBook more often than a traditional paperback textbook?

More Often	Less Often	Neither
○	○	○

Q11.

Did you read eBook/YouBook more or less often than a traditional paperback textbook?

How likely are you to purchase an eBook instead of a paperback textbook? What factors contribute to your decision?

Q12.

To what degree do you agree the following statements about using Enhanced WebAssign (EWA)?

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
EWA was easy to use.	○	○	○	○	○
EWA was easy to access.	○	○	○	○	○
EWA helped me to better manage my assignments.	○	○	○	○	○
EWA immediate feedback was essential to my learning.	○	○	○	○	○
The assignments and learning tools on EWA prepared me for my exams.	○	○	○	○	○
Using EWA improved my chances of passing my Mathematics course.	○	○	○	○	○
EWA helped me to improve my knowledge and understanding of Mathematical concepts.	○	○	○	○	○
I would recommend EWA to other students.	○	○	○	○	○
EWA is a valuable purchase.	○	○	○	○	○

Q13.

How did you communicate with your instructor outside of the class room?

- ☐ Email
- ☐ Phone Call
- ☐ Text Message
- ☐ WebAssign Private Message
- ☐ WebAssign Ask My Teacher
- ☐ Office Hours

Q14.

Where do you typically use Enhanced WebAssign (EWA)?

- ☐ On Campus: Computer Lab
- ☐ Home
- ☐ Work
- ☐ Other

Q17. Did your class meet in a Computer Lab?

- ◯ Only in a Computer Lab
- ◯ Computer Lab and a Classroom with Laptops
- ◯ Only in Classroom with Laptops
- ◯ Only in a Classroom without Laptops

Q18. Was it essential to meet in a Computer Lab or have access to Laptops during class? Why or Why not?

Q19. Did your instructor answer questions about your EWA assignment during class?

Yes	No
◯	◯

Q20. Did your instructor encourage you to complete your EWA assignments?

Yes	No
◯	◯

Q21. How did use you Enhanced WebAssign's "Show My Work" feature?

- ☐ Typed work directly into WebAssign
- ☐ Uploaded Pictures
- ☐ Uploaded some type of Word document

Q24.
On average, how much time a week did you spend completing EWA assignments outside the classroom?

- 0-2 hours
- 2-4 hours
- 4-6 hours
- 6-8 hours
- 8+ hours

Q25. What was your overall grade on WebAssign?

- 95+
- 90-95
- 85-90
- 80-85
- 75-80
- 70-75
- Less than 70

Q26. Did you or will you pass this Mathematics course?

Passed	Failed	Not sure yet
◯	◯	◯

Q27. While enrolled in this Mathematics course, were you a full time (12 or more credits) or part time student?

- Part time student
- Full time student

Q29. Ethnicity origin (or Race): Please specify your ethnicity.

- I Prefer Not to Disclose
- Black, Afro-Caribbean, or African American
- East Asian or Asian American
- Latino or Hispanic American
- Middle Eastern or Arab American
- Native American or Alaskan Native
- Non-Hispanic White or Euro-American
- South Asian or Indian American
- Other

Q30. Age: What is your age?

- Under 20 years old
- 20-25 years old
- 25-30 years old
- 30-35 years old
- 35-40 years old
- 40 years or older

Q31.
Please feel free to make any other comments about your experiences using Enhanced WebAssign (EWA)?

Q34. Was your class a Hybrid E-Learning course?

- Yes
- No

Q35. Was your class an ASAP block course?

- Yes
- No

Q36. Are you an ASAP student?

- Yes
- No

Q37.
Was the ability to track your attendance on EWA useful to you? Why?

Q38. Does using WebAssign work well with your learning style? Why or Why not?

Q39. Did you learn more or less in this class compared to other Mathematics' classes where you didn't use WebAssign? Why?